A PRELIMINARY ASSESSMENT OF POPULATION EXPOSURES RESULTING FROM TRUCK IDLING AT PORT GATES

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Alana Wilson

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A PRELIMINARY ASSESSMENT OF POPULATION EXPOSURES RESULTING FROM TRUCK IDLING

Approved by:

Dr. Michael O. Rodgers, Advisor
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Alexander Samoylov
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Randall L. Guensler
School of Civil and Environmental Engineering
Georgia Institute of Technology

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LIST OF ABBREVIATIONS

AB	Assembly Bill
AERMOD	American Meteorological Society/Environmental Protection Agency Regulatory Model
AIRS	Aerometric Information Retrieval System
AWOS	Automated Weather Observing System
BEIS3	Biogenic Emissions Inventory System version 3
Br	Bromine
CALINE	California Line Source Dispersion Model
CAL3QHC	CALINE3 with Queuing and Hot Spot
CARTEEH	Center for Advancing Research on Transportation Emissions, Energy, and Health
CMAQ	Community Multiscale Air Quality Modeling System
CO	Carbon monoxide
DEF	Diesel Exhaust Fluid
EC	Elemental Carbon
EJSCREEN	Environmental Justice Screening Tool
EMFAC	The Emission Factors Model
EPA	Environmental Protection Agency
ETS	Environment Tobacco Smoke
Fe	Iron
FOM	Figure of Merit
GIS	Geographic Information System
GPS	Global Positioning System
GT	Georgia Institute of Technology
HC	Hydrocarbon
ISCST3	Industrial Source Complex Short Term model version 3
ISH	Integrated Surface Hourly
IVE	International Vehicle Emissions
MM5	PSU/NCAR Mesoscale Meteorological Model
MOTREM	Montreal traffic model
MOVES	Motor Vehicle Emissions Simulator
Mn	Manganese
NAAQS	National Ambient Air Quality Standards
N/A	None Applicable
NCAR	National Center for Atmospheric Research
NIOSH	National Institute for Occupational Safety and Health
NO	Nitric oxide
NO2	Nitrogen dioxide
OC	Organic Carbon
OSPM	Operational Street Pollution Model
O3	Ozone
Pb	Lead
PM	Particulate Matter
RHCr	Ratio of Robust Highest Concentration

SCR	Selective Catalytic Reduction
SEP	Socioeconomic Status Position
SEM	Standard error of the mean
SMOKE	Sparse Matrix Operator Kernel Emissions Model
SO2	Sulfur Dioxide
TCEQ	Texas Commission on Environmental Quality
TEOM	Tapered Element Oscillating Microbalance
Ti	Titanium
μg	Micrograms
UTC	University Transportation Center
V	Vanadium
WRF	Weather Research and Forecasting Model
Zn	Zinc

SUMMARY

The work presented in this thesis is a contribution to a larger research effort studying emissions associated with port operations. The findings from this thesis will allow the CARTEEH project team create a study methodology and data analysis plan that best fits their purposes and gives the best insight into population exposures related to port emissions. The contribution of this work can be split into three components: literature review, population demographics mapping, and dispersion modeling. The literature review for this project includes looking at population exposure studies, studies with measurements of truck emissions, and existing efforts to reduce port emissions.

The population demographics mapping portion of this work includes mapping population demographics for areas surrounding the Port of Los Angeles, Port of Long Beach, Port of Houston, Port of Savannah, and Port of Brunswick. The data used for this section was taken from the US Census Bureau and from the EPA's EJSCREEN tool and includes data on income, race, housing occupancy, house and family size, age, linguistic isolation, and education.

The dispersion modeling component of this analysis looks at emissions from truck drivers queuing at part gates. These emissions were modeled in AERMOD on three different spatial scales and then mapped using ArcGIS's kriging interpolation tool. The modeling portion of this thesis evaluates the effect vehicle age, meteorological data, and characterization of the roughness parameter has on estimated concentrations. The AERMOD results showed that vehicle age has the biggest impact on estimated concentrations from idling emissions outside of port gates

1. INTRODUCTION

1.1. CARTEEH

In 2016, a consortium from Texas A & M, Johns Hopkins University, the Georgia Institute of Technology, University of Texas at El Paso, and University of California, Riverside proposed the establishment of the Center for Advancing Research on Transportation Emissions, Energy and Health (CARTEEH). This center is a Tier 1 University Transportation Center (UTC) with a focus on the Fast Act priority research area of 'Preserving the Environment'. The center serves as a hub for advancing research that addresses emissions in the context of public health. In addition to furthering transportation research, CARTEEH's primary contribution is promoting interdisciplinary collaboration between the transportation and public health sectors as experts from these two fields have not traditionally collaborated together before to this extent.

One of CARTEEH's first initiatives establishes a Cooperative Research Program consisting of six initial projects selected for their multimodal and interdisciplinary nature. These projects will leverage the strengths of each member university into several synergistic initiatives. The topics covered by these initial projects encompass health risks, transportation emissions, alternative fuel technologies, and population vulnerability related to air pollution.

1.2. Truck Emissions- Exposure Study in Ports

One of the six initial Cooperative Research Program projects funded through CARTEEH is a truck emissions-exposure study in ports. This project is a multilateral effort between Georgia Institute of Technology, University of California Riverside, and Texas A & M. The project encompasses several focus areas related to CARTEEH including: alternative technologies, emissions and energy estimation, data integration, and the potential for exposure and health impact assessments. In addition to encompassing several focus areas, the study also includes emissions from five different ports across the United States. These five ports are located in Georgia, Texas, and California and personnel from the three consortium members located near each port are leading the study at their local port.

Ports are an important focus for air quality studies as these areas are major transportation hubs for the import and export of goods. These facilities are prone to air quality concerns as a result of emissions from marine engines, freight and drayage trucks, rail operations, trucking, and cargo handling equipment. The impact of these emissions sources is poorly understood and thus, the health effects of these emissions on vulnerable populations is also poorly understood. This lack in understanding is the result of the limited number of studies on the interactions of emissions from different sources related to port activities.

Research teams have measured and modeled separately emissions from shipping, freight handling, trucking, and rail operations related to port operations. Little work has been done to combine these emissions sources into one holistic analysis. The first step in addressing poor air quality, is accurately estimating the concentrations these communities are exposed to. This improved exposure assessment can then be used to inform alterations made to port operations in order to improve air quality for these people.

There is a need for individual pollution assessments for the different port operations in order to conduct a comprehensive air quality assessment. Part of the assessment will include emissions inventories and modeling efforts for emissions from marine engines, freight and drayage trucks, rail operations, trucking, and cargo handling equipment. Such a large endeavor will be broken into smaller pieces conducted by different project members. The individual phases for the overall project consists of:

1. Literature Review: Researchers identify and evaluate the most relevant literature connected with: a.) Occupational and population exposure associated with port operations, b.) Reductions in particulate matter emissions related to port-based freight handling equipment.
2. Development of Measurement Plan: Each research team outlines a data measurement and collection plan that includes data quality assurance and quality control plans to ensure comparability between data sets.
3. Update and Expand Georgia Tech Fuel and Emissions Calculator: This expansion includes specific types of port equipment not currently available in the model.
4. Update GT Port Model: The update allows modeling specific features for each of the ports through the Georgia Tech Port/Rail model.
5. Field Data Collection: Conduct filed measurements of particulate matter concentrations with appropriate meteorological data collection at each of the ports selected. The research teams will also determine activity levels for port equipment and inventory this equipment.
6. Port modeling: Perform dispersion and emissions modeling using the data collected during the Field Data Collection campaign.
7. Final Project Report

The work outlined in this paper, is done in support of the overall project. This work contributes to the literature review, field data collection, and port modeling components of the overall project, with a focus on the contributions of trucking operations to port emissions.

1. 3. Trucking Operations near ports

Freight trucks often queue for long periods of time outside of ports generating heightened levels of emissions from idling in a concentrated area. These emissions are in addition to emissions from ships, freight handling equipment, and fugitive dust. Modeling the emissions of idling freight trucks is a key component to understanding the overall impact ports have on local air quality.

Modeling idling emissions generated from a defined area is a field of research that is not well understood. Many research questions still remain, and must be answered before any data collection at ports can begin. Missing data or low-quality data collection makes any data collected for this study of no value for answering the overall question of ports' impacts on air quality. A key contribution of this report will be refining the measurement plan for this study to ensure that all required data is collected. The scope of this report is too limited to prescribe a complete measurement plan; however, several key problems will be resolved as part of this work.

The key modeling questions this report addresses in relation to idling emissions include: (1). How do variations in truck model years influence concentrations? (2). How do different years' meteorological data influence concentrations? (3). How do different roughness parameters impact estimated concentrations? These questions will be further explored in Chapter 4 of this thesis

The overarching purpose of this project is to achieve a better understanding of the risks port workers and neighboring communities are at as a result of port activities. To better understand the risks of these populations, air quality data, meteorological data, activity data and other measures will be collected as part of the field study and then modeled and related to health indicators. The previous paragraphs discuss the questions still unanswered related to the modeling component of this project, but there are still questions related to health indicators used for this study.

Health impacts are often evaluated through a population exposure study. For population exposure studies, researchers determine the aggregate exposure of a selected population to air pollution (Watson, Bates, & Kennedy, 1988). Measuring concentrations of pollutants is a primary way researchers relate air quality to health risks for the exposed population. Understanding the make-up of the exposed population in addition to understanding their exposure to pollutants are equally important.

As part of understanding the make-up of exposed populations, it can be important to consider the Environmental Justice implications of port activities. The EPA defines Environmental Justice as, "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (United States Environmental Protection Agency, 2017). Understanding the ethnic, socio-economic, and other demographics of populations living near ports ensures that disadvantaged minorities are not unfairly and negatively impacted by port activities. This study uses census data to map the demographic characteristics of populations living near ports. These maps are used in conjunction with the air quality modeling efforts to help visualize the potential impacts ports have on the health of neighboring populations.

The study areas presented in this section will be further defined and explored, in the following sections of this thesis. The following sections will include a literature review, population demographics mapping, and modeling emissions generated by idling trucks.

2. LITERATURE REVIEW

This literature review covers three main topics:

1. Review of previous population exposure studies for populations near roadways and truck stops
2. Existing studies of emission reduction strategies at ports
3. Overview of existing dispersion models and model comparisons for modeling idling emissions

This literature review was developed by searching scientific reference databases and popular web search engines for key words from each of the three topics. From the relevant studies identified by the web-based search, other sources were identified based on references cited by the selected publications. As a first step to the formation of this literature review, an annotated bibliography of key literature was created.

In the first topic covered as part of the review, studies were selected that have measured truck and roadway-related human exposure to diesel exhaust. These studies measured particulate matter (PM) and in some cases other pollutants associated with diesel exhaust found to have negative health impacts. The studies included in this portion of the literature review also have an associated health indicator used to evaluate human response to measured concentrations of pollutants.

The second part of the review covers emission reduction strategies currently in use at ports and their reported success. The main types of emission reduction strategies reported include an appointment system for ports gates, extended operating hours for port gates, and other policy based emission reduction strategies.

The last part of the literature review focuses on existing dispersion models used for modeling idling emissions, with a focus on EPA approved regulatory models recommended for transportation project analysis. Air quality analysis for transportation projects requires thoughtful model selection as different models are better suited for different transportation project scopes. Project scope informs model selection, but model configuration can also heavily influence the results of population exposure studies. Components influencing study results based on model configuration include: source type, meteorology, and emissions factors and care should be taken when making decisions regarding these factors.

The following sections contain a synthesis of significant results for the three topics introduced above. For each of the three topics, the findings from selected studies are presented in either a tabular or paragraph form with a focus on the study methodologies for each paper. In addition to study methodology, results and key findings may also be presented depending on the primary purpose identified for each topic.

2.1 Population Exposure Studies Related to Roadways and Truck Stops

This section of the review builds the foundation for a study methodology detailing the measurement collection procedures for collecting data at each port. The studies presented in this section were identified for analyzing health impacts related to diesel-exhaust generated at roadways and truck stops. This section compares these studies based on study design, and air quality and health data collection methodologies. The findings from this review allows the CARTEEH project team to learn from other studies and create a study methodology for their project that best fits their purposes and gives the best insight into population exposures related to port emissions.

This section of the review aims to answer three questions:

1. How should air quality data be collected to be relatable to health?
2. What additional types of data should be collected (meteorology, etc.)?
3. What health indicator should be collected to coincide with the data?

In an effort to answer these three questions, several key parameters were identified to best characterize the methodologies employed by previous studies. The methodologies were split into health-specific and air quality data collection procedures. Key study characteristics for the air quality data collection procedures include: study duration, location, equipment used, parameters measured, meteorology data collected and number of monitoring locations. Key study characteristics for health-specific data collection procedures include: study duration, number of participants, health indicator used, and air-health relationship employed. The variations in these study characteristics are summarized in *Table 1*, for each of the eleven studies included in this section of the review. A brief summary of the scope of each study has also been included for reference

.Table 1: Population Exposure Studies Related to Roadways and Truck Stops

Study		(Dockery, 1993)	(Gripshun, 2013)	(Lwebuga-Mukasa, 2004)
Scope		Related mortality and air quality across 6 US metropolitan areas	Measured actual improvements in air quality from emissions controls and public perceptions of improvements	Analyzed the spatial variation of asthma cases and their associated proximity to major transportation corridors.
Air Quality Data	Duration	1979-1985 (7 years)	2002-2005, 2010-2011 (6 years)	1991-2000 (10 years)
	Location	Portage, WI; Topeka, KS; Harriman, TN; Watertown, MA; St. Louis, MO; Steubenville, OH	Cincinnati, OH	Peace Bridge, Buffalo, NY
	Parameters Measured	Total particles, sulfur dioxide, nitrogen dioxide, ozone, aerosol acidity, sulfate particles	PM2.5, EC, OC, Ti, V, Mn, Fe, Zn, Br, Pb	Yearly volume of truck and bus traffic; traffic data used as surrogate to air pollution
	Meteorology	N/A	Wind speed and direction	wind direction
	Monitoring Locations	6	4	No air-monitoring facilities
	Equipment	Centrally located air-monitoring station	MS&T Area Sampler/Harvard-type PM2.5 impactor	Airport weather station
Health Data	Duration	17 years with 14-16 year follow-up period	2002-2005, 2010-2011 (6 years)	Variable
	Participants	811	100	N/A
	Health Indicator Used	Life survival probabilities; mortality-rate ratios; Cox proportional-hazards regression models	Public perception of air quality surveys	Hospital discharges for asthma (1991-1996), hospitalizations and outpatient visits for asthma (1995-2000)
	Air Health Relation	Mortality rates	N/A	N/A
Additional Data		N/A	N/A	Population, median household income, percentage of renter-occupied housing units, average household income, race/ethnicity, age brackets, education level, year homes were built

Table 1: (continued) Population Exposure Studies Related to Roadways and Truck Stops, Studies 4-6 of 11

Study		(Mauzerall & Tong, 2007)	(Ryan, 2005)	(Rudell, 1994)
Scope		Looks at mortalities related to ambient concentrations of ozone and PM2.5 in the U.S. using CMAQ	Conducted health surveys for parents of infants living near highway truck traffic reporting the prevalence of wheezing	Researchers exposed humans to diluted diesel exhaust and measured the effect on lung function
Air Quality Data	Duration	January & July 1995 & 1996	Not indicated, but at least 1 year	1 hour
	Location	US	Cincinnati, OH	Sweden
	Parameters Measured	Emissions obtained from US EPA national emission inventory 1995 and the BEIS3	Proximity of infant's home to federal interstates, state routes, and bus routes, speed limit on the roadway, and traffic volume	CO, NO, NO2, PM, formaldehyde
	Meteorology	NCAR MM5 meteorology	N/A	Controlled exposure chamber
	Monitoring Locations	N/A	N/A	~3 per pollutant
	Equipment	CMAQ	ArcView	Miran 1-AIR instrument, CSI 1600 Oxides of nitrogen analyzer, FID Instrument 3-300, condensation particle counter model 3022
Health Data	Duration	January & July 1996	Not indicated, but at least 1 year	1 hour
	Participants	US population	622 infants 6 months or older and screened for allergy symptoms	8 healthy non-smoking patients age 19-27 years old
	Health Indicator Used	Incidence of mortality or respiratory disease; used two epidemiological studies for analysis	Parent reported wheezing without symptoms of a cold	Self-reported symptoms of headache, nausea, tiredness, tightness of chest, coughing, difficulty breathing, eye irritation, nasal irritation, throat irritation
	Air Health Relation	Incidence of mortality with and without presence of anthropogenic emissions	Presence of wheezing when located within 400 meters of a major road	Lung function tests performed before and after the experiment;
Additional Data		N/A	N/A	N/A

Table 1: (continued) Population Exposure Studies Related to Roadways and Truck Stops, Studies 7-9 of 11

	Study	(Smargiassi, 2006)	(Laden, Hart, Smith, & Davis, 2007)	(Emmelin, Wall, & Nystrom, 1993)
	Scope	This study looked at associations between traffic emission exposures and respiratory disease among the elderly	Retrospective cohort study looking at exposure-related mortality in the unionized trucking industry	Indirect exposure measurements for Swedish dock workers based on estimated diesel exhaust exposure times
Air Quality Data	Duration	April 2001-March 2002	5-day sampling period at one site per month from 2001-2005	1957-1979
	Location	Montreal, CA	US truck freight terminals (36)	Sweden
	Parameters Measured	Traffic Volume	PM2.5, EC, OC	Machine time, fuel consumption
	Meteorology	N/A	Temperature, humidity, wind direction, wind speed	None
	Monitoring Locations	N/A	Not stated	15 Ports
	Equipment	Used MOTREM98 to estimate weekday traffic intensity based a phone-survey	PM2.5 collected on 37-mm Teflon; EC and OC determined by NIOSH 5040 method	None- used company records to obtain fuel use and machine hours information
Health Data	Duration	April 2001-March 2002	1985-2000	1957-1982
	Participants	35309 hospital patients	54319 males	154 dock workers
	Health Indicator Used	Hospital admission of people over age 60 for respiratory diagnoses	Cause-Specific mortality using the National Death Index	Lung cancer
	Air Health Relation	Proximity of home to a major roadway	Questionnaire for workers to assess smoking status, job title, and terminal characteristics	Lung-cancer in relation to exposure time based on annual fuel diesel consumption
	Additional Data	Included case and control hospitalizations in their study	Collected information about job titles and duties, vital status, date of death, cause-specific mortality focusing on lung cancer, bladder cancer, ischemic heart disease, and obstructive lung disease	Smoking information, employment history

Table 1: (continued) Population Exposure Studies Related to Roadways and Truck Stops, Studies 10-11 of 11

Study		(Gauderman, 2007)	(Morgenstern, 2007)
Scope		Study analyzed the relationship between exposure to traffic emissions and the growth of lung-function over a 8-year period	Looked at air quality and infant respiratory health in Munich, City Germany.
Air Quality Data	Duration	1993-2003	March 1999-July 2000; measurements made in 2 week intervals with air sampled for 15 minutes every 2 hours
	Location	12 southern California communities	40 sites throughout Munich City
	Parameters Measured	Average hourly concentrations of O3, NO2, PM10, 2-week integrated filter samples for acid vapor, and PM2.5 mass and chemistry, EC, OC	PM, NO2
	Meteorology	Wind speed, wind direction, atmospheric stability, mixing heights	None mentioned
	Monitoring Locations	1 per community (12 total)	40 traffic and 40 background sites with four measurements taken per site, one per season for each site
	Equipment	CALINE4; Used roadway volumes, traffic volumes, meteorological conditions, and vehicle emission rates as well as	Harvard Impactors using Anderson Teflon membrane filters, Smoke Stain Reflectometer, Palmes tubes for NO2 measurements
Health Data	Duration	8 years (one group began study in 1993, the other in 1996)	1990-1992
	Participants	3677 children	3577 newborns from Munich and Wesel
	Health Indicator Used	Lung-function measurements/growth using spirometry	Questionnaires completed by parents every 6 months documenting coughing, wheezing, asthma, etc.
	Air Health Relation	Lung-function in relation to traffic exposure based on distance of each child's home from a major roadway	Used GIS to assess traffic-related air pollution concentrations at each child's home and related this to respiratory symptoms
Additional Data		Conducted annual surveys for race, parental income and education, history of doctor-diagnosed asthma, exposure to smoking, pets and ETS	Also included parental atopy, sex, maternal education, siblings, use of gas for cooking, home dampness, mold, pets, ETS

From looking at the air quality data collection durations presented in Table 1, data collection periods ranged from 1 hour of data collection to 23 years of collecting data. Many studies that used air quality data sampled at the same location over several years' period, used the data collected by permanent, centrally located air-monitoring stations (Dockery, 1993) (Mauzerall & Tong, 2007). Many local air quality divisions have continuous monitoring networks already established and publish the data collected by these stations, making it possible for studies to focus on analyzing this data and collecting correlated health data.

Studies with a focus on spatial trends and spatial variance in air quality data typically collected data over shorter time periods (typically several days or weeks) because data collection occurred at multiple sites. The spatial scale of these studies ranged from city-wide (Morgenstern, 2007) (Gripshun, 2013), to regional scales (Dockery, 1993) (Gauderman, 2007), to country-wide scales (Laden, Hart, Smith, & Davis, 2007).

In addition to the varying spatial scales of the studies presented, there was even more variety in the number of monitoring locations included at each site. Some studies collected data from one central location per site, others put samplers in several locations, and some took personal air quality data, background air quality data and ambient air quality data on site. Both of the city-wide studies collected four measurements per site, but in on study they moved around to different sites within the city and collected one measurement per season at each site (Morgenstern, 2007), whereas the other city-wide study used four permanent monitoring locations (Gripshun, 2013). The CARTEEH ports study is conducting an analysis on a scale similar to a city-wide study; however, there seems to be no established best practice for collecting data on this scale, so the research team will need to devise a data collection plan that best captures occupational and population exposures given the equipment and personnel constraints of their team.

Of the studies that collected their own air quality data, particulate matter (PM)/total particles is the only parameter measured by every study. Measuring PM was most commonly accomplished using Harvard Impactors or cyclone separators fitted with a Teflon filter. Some studies specifically collected PM10, PM2.5 or PM1 air quality data. Elemental carbon, organic carbon, nitrogen oxide, nitrogen dioxide and aerosol acidity data were also collected by some studies. There seems to be less agreement between the studies about which pollutants, in addition to PM, are important to collect for health studies; however, there did seem to be a unanimous agreement that PM data should be collected for air quality studies focused on diesel emissions and relating these emissions to a health effect.

For meteorology data collection, wind speed and wind direction were the parameters most consistently included in the data collection process. Some of the studies also included temperature and humidity data (Laden, Hart, Smith, & Davis, 2007) as well as atmospheric stability mixing heights (Gauderman, 2007). This additional meteorological data was collected by studies with a larger spatial and temporal scale, indicating this data may be important for correlating data collected in different areas and in different seasons. The CARTEEH ports study will include data from Georgia, Texas, and California so additional meteorological data may be required to account for varying climates across the three study locations.

From looking at the literature from previous air quality studies that also incorporated a health indicator, many studies used traffic data as a proxy for air quality data (Lwebuga-Mukasa, 2004) (Ryan, 2005) (Smargiassi, 2006). These studies used traffic volume or intensity and associated roadway emissions to estimate population exposures in the given study area.

Many studies used proximity to heavy traffic areas as a link between air quality and health (Lwebuga-Mukasa, 2004) (Ryan, 2005) (Smargiassi, 2006) (Gauderman, 2007) (Morgenstern, 2007). This link is based on GIS analysis of proximity of the study participants' homes to different roadway classes and the associated traffic emissions for each roadway. Roadways were classified based on traffic volume or intensity and emission values were assigned to these roadways in accordance to their classification. Study participants' exposure was characterized by incremental distance from a roadway and roadway type. Of these studies that linked health and proximity to a major roadway, questionnaires and hospital admissions were the most popular link between respiratory health and exposure.

A negative health effect was typically identified by asthma, wheezing and coughing (Lwebuga-Mukasa, 2004) (Ryan, 2005) (Morgenstern, 2007). Two of the studies physically measured lung function and growth of lungs for children using spirometry; however, this method seems less popular for larger studies as it requires specialized equipment, trained personnel and is time intensive for data collection (Rudell, 1994) (Gauderman, 2007).

One of the eleven studies presented in this section, looked specifically at population exposures related to ports, and is presented in *Table 1* (Emmelin, Wall, & Nystrom, 1993). This study looked at 15 Swedish ports' records of machine times and fuel consumption and estimated occupational exposures based on this data without physically collecting any air quality data. To link workers exposure to a health effect, they included lung cancer diagnoses and smoking history for the port workers. While extensive health and air quality data were not included in the study, they were able to link exposure to diesel exhaust at ports to increased odds of respiratory disease. These correlations between respiratory disease and heightened exposure to diesel exhaust were made in 1993, indicating a need for more current studies of occupational exposures for port workers using improved methods of evaluating occupational exposures. Evaluation of occupational exposures in the trucking industry are more prevalent than for the port industry as shown by the studies presented in this section, emphasizing a need for the CARTEEH Ports Study.

Based on the methodologies employed by these eleven studies, collecting information on workers' history of respiratory disease, smoking status, and occupational history seems to be the most pertinent health information to collect. Including information about job title, years of employment in each job, and each jobs' associated exposure based on background concentrations and personal exposure monitors is important for linking health history to personal exposure. Once exposures associated with each job title are evaluated, a follow-up study or retrospective study could link job specific exposures to health outcomes. It may be possible to use historical emissions data and employment data with the fully developed port model to look at past workers estimated exposure and then look at their current health records to link the two. This type of retrospective cohort study could be useful to evaluate which job types show the highest correlation to a negative health outcome and should be the first to consider strategies to improve air quality in these job functions.

2.2. Existing Studies of Emission Reduction Strategies at Ports

This section looks at existing studies of emission reduction strategies at ports. The previous section presented a need for evaluating occupational exposures and associated health outcomes for different job titles and the possibility of making improvements for the jobs found to have the highest correlation to a negative health effect. This section looks at measures different ports have taken to improve air quality and reduce emissions in different sectors of port operations. Many of these strategies are policy based; however, some do include technology retrofits in their improvement plans.

Many studies evaluated the use of gate appointment systems or some variation of this type of scheduling system. Gate appointment systems require trucks to schedule their freight deliveries at ports in an effort to minimize numbers of idling trucks and the time each truck is waiting to drop-off freight. Improvements to port freight delivery system were mandated in California under California Assembly Bill 2650. The aim of this bill is to reduce idling emissions by giving ports the option to either extend their hours for freight pick-up and drop-off, institute a gate appointment system, or propose other solutions to reduce the frequency and duration of truck idling at port gates (Giuliano & O'Brien, October 2007). Following the implementation of this idle reduction bill, a 16-month monitoring period commenced to assess the effectiveness of the bill at reducing idling. The results of the monitoring period indicated the appointment system did not reduce waiting times for trucks nor reduce the numbers of trucks waiting and thus they saw no emissions reductions. The study indicated that terminals did not favor the appointment system and so they did not make the appointment system appealing to drivers, making this system an under-utilized addition to port operations. This under-utilization of the appointment system could be a primary reason no improvements were seen, indicating that future efforts need to have terminal operators and key stakeholders on-board and that the appointment system needs to add value to port operations apart from emissions reductions.

As a follow-up study to the implementation of the appointment system under AB 2650, one research team analyzed the improvements added to the appointment system by using an optimization-based scheduling framework to help optimize drayage operations (Namboothiri & Erera, 2008). The gate appointment system as is adds constraints to drivers' schedule and limits the number of drop-offs and pick-ups they can make. The study recommends that drayage firms use a decision support approach to optimize their operations when using an appointment system.

An analytical point-wise stationary approximation model is an example of a decision support system that can be utilized to either assign appointment times using a quota-limited system that assigns truckers other time windows if their preferred delivery time is unavailable (Chen, Zhou, & List, 2011). An alternate method, which uses the same system and may help reduce scheduling constraints for drivers is a toll system that assigns toll values based on demand for an appointment time. Utilization of a decision support approach can help improve the perception of appointment systems, thus increasing the utilization of these systems and reducing idling emissions at port gates.

The examples of decision support systems provided in the previous paragraph were devised with operational efficiency as the main objective. In addition to operational efficiency, emissions reductions are also important to consider. One study looked at the use of a queueing network based bi-objective model and quantified the reductions in idling emissions associated with diverting truck arrivals away from high demand appointment times (Chen, Govindan, & Golias, 2013). The study found when they shifted 4% of truck deliveries or pick-ups to non-peak hours emissions from truck idling were reduced by as much as one-third of the total emissions. The use of this type of system has significant emissions reductions.

A study prepared for the Canadian Transportation Development Center evaluated the effectiveness of gate appointment systems in reducing port emissions at North American ports and also considered the use of automation technologies and extended gate hours (Morais & Lord, March 2006). This study found that gate appointment systems and extended operating hours were successful in reducing truck emissions at the Port of Vancouver, in contrast to the failure of the appointment system at the Port of Los Angeles and Port of Long Beach.

The implementation of an appointment system at the Port of Los Angeles, Port of Long Beach, and Port of Oakland mandated under AB 2650 demonstrates the potential of environmental policy to improve air quality; however, this bill was under-supported by key-stakeholders with significant economic and political influence and so the potential benefits of the bill were not achieved (Giuliano & O'Brien, October 2007). In spite of the limited success of this regulation, ports in New York, New Jersey, and Vancouver, BC are in various phases of implementing these appointment systems or limiting idling periods to a 30-minute period with a fine issued for idling beyond this time frame. Additionally, 20 other states have municipal idling regulations in place and use policy to reduce emissions and improve air quality (Morais & Lord, March 2006). Other ports have already switched to lower emission dock vehicles instead of an appointment system as this alternative is seen as having a greater potential for reducing emissions from port operations (Giuliano & O'Brien, October 2007).

The Pier Pass Program was implemented on July 23, 2005 at the Ports of Lost Angeles and Long Beach and operates similar to extended idling hours. The Program adds nighttime and weekend hours to delivery hours schedule and incentivizes deliveries made during these hours. Shifting deliveries to nights and weekends reduces traffic and congestion during peak daytime hours and allows truckers to make more deliveries on average. This system was favorable to a majority of truck drivers interviewed and reduced the idling time and thus emissions generated by vehicles making deliveries ((Morais & Lord, March 2006).

Cargo handling equipment also generate emissions when fueled by conventional crude diesel fuels. Studies have found that low sulfur diesel fuel, diesel emulsions, biodiesel and Fischer-Tropsch diesel are all viable alternatives to fuel cargo handling equipment that have reduced emissions (Soloman & Bailey, 2004). The study found that the PM emissions reductions for these fuels can range from 3-63% with an extra cost ranging from $0.05-$1 per gallon (USD).

All of the studies discussed in this section provide alternatives to reduce truck idling times and volumes outside of port gates. These alternatives range in their scale of complexity, cost, and favorability with drivers and terminal operators. One of the main systems currently implemented is an appointment system which has seen various levels of effectiveness but is shown to be effective if implemented with the support of stakeholders and with the use of a carefully evaluated scheduling or toll system. The findings of these studies indicate that emission reductions from vehicles idling at port gates are feasible with simple policies and simple but well-designed systems.

2.3. Comparison of Commonly Used Air Quality Dispersion Models

This section of the literature review explores different air quality models and model configurations, and makes initial decisions about which model and configuration best suits this study. The studies presented in this section were identified for modeling population exposures related to diesel-exhaust generated by roadways and truck stops. The studies selected were then compared based on model used, air quality data used, and data evaluation methodology. The findings from this review allows the CARTEEH project team to learn from other studies and create a study methodology and data analysis plan that best fits their purposes and gives the best insight into population exposures related to port emissions.

In an effort to assess different air quality models, several key parameters were identified to best characterize the methodologies employed by previous studies. The methodologies were split into air quality data collection procedures and modeling specifications. The study characteristics identified as key for the air quality data collection procedures include: study duration, location, equipment used, parameters measured, meteorology data collected and number of monitoring locations. For modeling specifications, the key study characteristics identified include: software used, parameters modeled, findings, and data evaluation method. The variations in these study characteristics are summarized in Table 2 for each of the nineteen studies included in this section of the review. A brief summary of the scope of each study is included in the tables for reference.

Table 2: Comparison of Different Study's Application of Commonly Used Air Dispersion Models

	Study	(Benson, 1992)	(Chen H. , 2008)	(Davis, et al., 2006)
	Scope	Provides a history of the development of the CALINE models and evaluates CALINE3 and CALINE4 using five field studies.	Looks at an intersection in Sacramento, CA and a road in London, UK to compare the different model results to observed concentrations of PM2.5.	Used data collected from trucking terminals to evaluate structural equation modeling to predict personal exposure.
Data Collection	Duration or Data Time Period	Used data from General Motors Sulfate Dispersion Experiment, Illinois EPA Freeway/Intersection Study, EPA NO2/O3 Sampler Siting Study, Caltrans Intersection Study, and the Caltrans Highway 99 Tracer Experiment for model validation.	3 days for one site, 253 hours from July 31, 1998- July 17, 2000	2001-2005
	Location		Sacramento, CA and London, UK	36 trucking US terminals
	Parameters Measured		PM2.5	PM2.5, EC, OC
	Meteorology		Depended on model requirements	Temperature, humidity, wind direction, wind speed
	Monitoring Locations		4 between two studies	4: personal monitoring, 2 indoor work locations, background
	Equipment or Data Used		Not indicated	PM2.5 collected on 37 mm Teflon filter; PM1 collected on 22 mm Quartz tissue filter
Modelling Specifications	Software	CALINE3, CALINE4	AERMOD, CALINE3, CALINE4, CAL3QHC	STATA Version 8.2 (statistical model)
	Parameters Modeled	Varied by case study	PM2.5	PM2.5, EC, OC
	Findings	CALINE4 showed modest improvements in the accuracy of its predictions in comparison to CALINE3	In Sacramento, AERMOD under-predicted PM2.5 and CALINE4 and CAL3QC performed relatively well. In London, CALINE4 and CAL3QC were unsuitable- complex meteorology from the street canyon effect.	Statistically significant results and high R2 value supports the application of the SEM approach to personal and population exposure modeling
	Data Evaluation Method	Overall figure of merit (FOM) for six component statistics, scatterplots and relative error plots	Factor-of-Two plots, difference overview and patterns, correlation, prediction bias, prediction trend	Cross-validated background exposure measurements with EPA Air Quality System monitoring data

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 4-6 of 19

Study		(Faulkner, Shaw, & Grosch, 2008)	(Garcia, 2007)	(Grosch & Lee, 1999)
Scope		Determined the sensitivity of AERMOD to various inputs.	Analyzed the air quality effects of wind on transporting particles to truck freight terminals	Evaluates model response to variations in albedo, Bowen ratio, and surface roughness length
Data Collection	Duration/Data Period	1- and 24-hour modeling period	1 month sampling from July 2002-August 2003; 12-hour samples	1987
	Location	Amarillo, TX	11 US trucking freight terminals	Wichita and Topeka, KS
	Parameters Measured	N/A	PM2.5, EC, OC	N/A
	Meteorology	Albedo, Bowen ratio, surface roughness, barometric pressure, solar radiation, wind speed, average wind direction, temperature, relative humidity, sky cover	Wind direction, wind speed, temperature, and relative humidity	Albedo, Bowen ratio, surface roughness
	Monitoring Locations	N/A	1	2
	Equipment or Data Used	N/A	Davis Weather Monitor II, Harvey Field Monitor, 37-mm Teflon Filter, 25-mm quartz tissue filter	Upper air MET station in Topeka, KS, and surface observation station in Wichita, KS
Modelling Specifications	Software	AERMOD, ISCST3	Intercooled Stata Version 8.2	AERMOD, BREEZE AERMET
	Parameters Modeled	PM	Wind direction and weighted concentrations of PM2.5, EC, and OC	Various concentrations for emissions generated by ground sources and various stack heights
	Findings	AERMOD was found to be sensitive to: changes in albedo, surface roughness, wind speed, temperature and cloud cover but not to Bowen ratio.	The results did not conclusively support the idea that upwind sources have the effect of elevating background concentrations of trucking facilities (only proved true at 3 of 11 facilities)	Highest concentrations from surface sources occurred when land use parameters for water were used; concentrations only varied significantly in relation to surface roughness; albedo and Bowen ratio had little effect
	Data Evaluation Method	Sensitivity analysis	Directional mean, Wilcox Rank-Sum	Direct comparison of values

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 7-9 of 19

	Study	(Kesarkar, 2007)	(Liu, Wang, Chen, & Han, 2013)	(Liu H. , Xu, Rodgers, & Guensler, 2015)
	Scope	Used the WRF Model to fill in planetary boundary layer and surface layer parameters in AERMOD	Used GPS data from taxis in Shanghai to extract vehicle operation data to create an emission inventory in MOVES.	Looks at the effect project-specific vehicle classifications have on results in MOVES compared to internal assumptions in MOVES.
Data Collection	Duration/Data Period	April 13-17 2005	June 29-July 15 2012	Spring 2012
Data Collection	Location	Pune, India	Shanghai, China	I-85 near Atlanta, GA
Data Collection	Parameters Measured	PM10	Time, instantaneous speed, GPS location of 29,100 taxis	Vehicle counts/classifications
Data Collection	Meteorology	Wind direction, wind speed, rainfall	Obtained from Shanghai Meteorological Bureau	N/A
Data Collection	Monitoring Locations	4 (one background)	10	N/A
Data Collection	Equipment or Data Used	Low volume samplers with Teflon filters	Environmental Protection Bureau air monitoring sites; Taxi GPS	High definition video cameras with plate analysis equipment
Modelling Specifications	Software	AERMOD, WRF model	AERMOD, MOVES	MOVES
Modelling Specifications	Parameters Modeled	Vertical profiles of wind speed lateral and vertical turbulent fluctuations, temperature gradients, and PM10	HC, CO, and NOx	CO, CO2, HC, NOx, PM2.5,
Modelling Specifications	Findings	AERMOD generally underestimated concentrations of PM10 over the city.	AERMOD under-predicts NO2 concentrations, but this is not explicitly attributed to model performance. Updated emission factors improved the correlation of results with measurements	Need to use locally derived vehicle class inputs to use in MOVES for transportation project analyses
Modelling Specifications	Data Evaluation Method	Correlation, standard deviation, day-to-day variations in patterns of PM10 estimations	Correlation and sensitivity analysis	Sensitivity study

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 10-12 of 19

Study		(Liu H. , Xu, Rodgers, Xu, & Guensler, 2017)	(Miller , Fu, Hromis, Storey, & Parks, 2011)	(Tong, Mauzerall, & Mendelson, 2007)
Scope		Analyzes a method of integrating CALINE4 and AERMOD with the MOVES matrix in a distributed computing cluster.	Air quality study at an intersection of I-40 in Tennessee that included daily traffic emissions and idling emissions from a large truck stop.	Examines an integrated air quality assessment model that incorporates emissions, transport, chemical transformation, and human exposure into one model.
Data Collection	Duration/Data Period	January- December 2011	January-June 2005 (5 months)	July 1996
	Location	Suburbs of Atlanta, GA	Watt Road interchange on I-40 in Knoxville Tennessee	Continental US
	Parameters Measured	Traffic volumes, operating speeds	PM2.5, PM10	Hourly O3
	Meteorology	Wind speed, wind direction, temperature, and humidity	Wind speed, wind direction	MM5 Meteorology
	Monitoring Locations	N/A	One ramp site, one ridgetop site	48 simulations (one per state)
	Equipment or Data Used	Video cameras with plate analysis, NaviGAtor machine vision system	TEOM, E-BAM beta gauge instrumentation	Measurements from the Aerometric Information Retrieval System (AIRS),
Modelling Specifications	Software	AERMOD, CALINE4, MOVES	MOBILE (MOVES precursor)	CMAQ, NCAR MM5, SMOKE
	Parameters Modeled	CO, PM10, PM2.5	Roadway and idling emissions	NOx, O3, human exposure
	Findings	AERMOD predictions were lower than CALINE4 predictions; attributed to AERMOD's higher resolution meteorology data	Used an emission rate of 3.68 g/h for idling trucks; found that in a day 20% of emissions were from trucks on the interstate and 80% were from idling	Identical increases in NOx produce different levels of O3 production resulting in total mortality levels that vary by a factor of 10
	Data Evaluation Method	Correlation and sensitivity analysis	Compared to NAAQS levels for PM and to background levels for that area	Mean normalized bias, mean normalized error, and unpaired peak prediction accuracy for surface O3 variations across the US as compared to hourly O3 measurements from AIRS

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 13-15 of 19

	Study	(Vallamsundar & Lin, 2012)	(Wang, Van den Bosch, & Kuffer, 2008)	(Wu, Song, & Yu, 2014)
	Scope	Provides a detailed process for performing transportation conformity analyses for PM non-attainment or maintenance areas	Explores micro-scale air quality modeling from traffic-induced air pollution in urban areas at the street-level	Investigation of the feasibility and limitations of developing a site-specific emission database for MOVES
Data Collection	Duration/Data Period	2011-2040 model years	September-November 2007	2001-2009 model year vehicles
	Location	Joliet, Illinois	Hague, Netherlands	Beijing, China
	Parameters Measured	Vehicle activity, fleet composition, vehicle age distribution	Street width, street length, vehicle type, vehicle speed, traffic volume, building height; hourly NO, NO2, O3 and PM10	N/A
	Meteorology	Temperature, humidity	Wind speed, wind direction, ambient temperature	N/A
	Monitoring Locations	2	4	N/A
	Equipment or Data Used	Traffic counters	Data from National Institute for Public Health and the Environment, the Netherlands Archive	N/A
Modelling Specifications	Software	AERMOD, MOVES	OSPM, GIS	MOVES
	Parameters Modeled	PM2.5	NO2, PM10	HC, CO, and NOx
	Findings	Highest concentrations were located near high volume areas in the direction of prevailing winds; changing the urban population had negligible effects on concentrations estimated	NO2 exceed limit values for all 4 areas, but for PM10 values were below the limits for all 4 areas	HC and CO emission rates constant with model year but NOx emissions decrease with model year (due to more stringent emission standards). With respect to age group, emission rates increase for all pollutants with varying slopes.
	Data Evaluation Method	None indicated	None indicated	Sensitivity analysis, linear regression

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 16-17 of 19

Study		(Wu & Niemeier, 2016)	(Yura, Kear, & Niemeier, 2007)
Scope		Examined the transportation conformity hot-spot analysis process in AERMOD	Looks at CALINE4's ability to model PM2.5
Data Collection	Duration/Data Period	2008-2012	3 days for one site, 253 hours from July 31, 1998-July 17, 2000
	Location	Corpus Christi, TX	Sacramento, CA and London, UK
	Parameters Measured	N/A	PM2.5
	Meteorology	AERMET files from TCEQ	Depended on model requirements
	Monitoring Locations	N/A	4 between two studies
	Equipment or Data Used	N/A	Not indicated
Modelling Specifications	Software	AERMOD	CALINE4
	Parameters Modeled	PM2.5	PM2.5
	Findings	Modeling roadway emissions as an area source opposed to a volume source is more appropriate and high-resolution receptor placement gives more accurate results.	CALINE4's performance for predicting PM2.5 concentrations is not optimal in heavy traffic areas. CALINE4 is also not recommended for use in areas with complex topography.
	Data Evaluation Method	Comparison test	Factor-of-Two plots

Table 2: (continued) Comparison of Different Study's Application of Commonly Used Air Dispersion Models, studies 18-19 of 19

	Study	(Zhang, Wei, Tian, & Yang, 2008)	(Zou, Zeng, Liu, Zhang, & Qiu, 2010)
	Scope	Looked at GIS-based methods of performing an urban-scale emissions inventory of SO2, NOx, and PM10	Assesses the sensitivity of AERMOD for different model options (urban vs. rural, elevated vs. flat terrain) when predicting SO2 concentrations.
Data Collection	Duration/Data Period	2004	2001-2003
	Location	Hangzhou, China	Texas
	Parameters Measured	Fossil fuel consumption, vehicle activity data, equipment running time	SO2
	Meteorology	Temperature, upper air meteorological data	2002 Integrated Surface Hourly (ISH) database, Radiosonde (RAOB) database
	Monitoring Locations	7	3
	Equipment or Data Used	Monitoring stations throughout the city	TCEQ air quality monitoring sites, 2002 National Emission Inventory
Modelling Specifications	Software	AERMOD, GIS, International Vehicle Emissions (IVE) Model	AERMOD
	Parameters Modeled	SO2, NOx, PM10	SO2
	Findings	SO2 and NOx estimations were reasonably close to measured concentrations for 5 of the 7 sites. PM10 estimates were much lower than observed concentrations due to exclusion of second PM10 data	Meteorological conditions do noticeably influence the performance of AERMOD, but the model is able to produce acceptable results without terrain data or when surface dispersion conditions are uncertain.
	Data Evaluation Method	Relative error between observations and simulated concentrations	Quantile-Quantile plots, bias, Index of Agreement, Correlation, ratio of robust highest concentration (RHCr),

Looking at the data duration and time period of data for the studies included in Table 2, the studies ranged from using several days of data, seasonal data, years, and even decades of data. Additionally, some studies collected their own air quality data to use in their study; whereas, other studies used data provided by local air quality monitoring stations which is publicly available data.

Similar to the data periods, the study locations also varied broadly. Several studies were conducted in countries other than the US or were US studies using data collected internationally in India, China, England, and the Netherlands. This variation in data sources may indicate some variation in the quality of data collection equipment or methods, but it also provides a diversity of exposure levels to test the models with. Many developing countries have less stringent emissions standards and do not have as advanced of emission control technologies so including these studies helps indicate how different models perform in extreme conditions or in environments with higher levels of pollutants than are found in the US. For example, a study in Pune, India used AERMOD to estimate PM10 concentrations across the city in a region prone to high levels of pollutants (Kesarkar, 2007). One study used models developed by the US EPA and then adjusted these models for application in China, as Chinese vehicle emission standards are less stringent than those in the US, and found new emission factors are needed to apply a US based model in other countries (Liu, Wang, Chen, & Han, 2013). Many of the studies conducted using data from China, were focused on using MOVES and GIS to model air quality there and were less focused on air quality dispersion models recommended by the US EPA (Wu, Song, & Yu, Sensitivity analysis of emission rates in MOVES for developing site-specific emission database, 2014) (Zhang, Wei, Tian, & Yang, 2008).

Of the nineteen studies presented in this section, eight of the studies collected PM (PM2.5 and PM10) data for air quality model development or evaluation. NOx, ozone, SO2, EC, and OC are other pollutants commonly used to evaluate model performance. Of the eight studies that collected PM data, two of the studies used AERMOD, two used STATA, two used MOVES/MOBILE, and two used CALINE3 or CALINE4 for modeling their data.

The studies that collected their own PM data and then used their data for air quality modeling differ from the studies discussed in this paragraph as these studies did not collect PM data, but did model PM using a dispersion model. Fourteen of the nineteen studies modeled PM but did not all collect air quality data, with nine studies using AERMOD to model PM, one study modeling PM with STATA, four studies using MOVES/MOBILE for PM modeling, and four studies using CALINE to model PM. Other studies used ICST3, OSPM, GIS, and IVE to model PM concentrations. As indicated by the results from the table, AERMOD is one of the most commonly used programs for modeling PM as it is the regulatory model approved by the U.S. EPA, but MOVES and CALINE are also commonly used for modeling PM.

Some studies used the air quality data collected to generate inputs required by the dispersion model they used. Other studies used the air quality data they collected to evaluate the performance of their model in predicting concentrations of various pollutants. The most commonly used method for evaluating model performance was looking at the correlation between modeled and measured concentrations with eight studies using this technique for data evaluation. Sensitivity analysis was another common data evaluation method with four studies using this technique.

Based on the findings from this portion of the literature review, AERMOD and CALINE will be the two models considered for the CARTEEH Ports Project. Model selection procedures will be further discussed in Chapter 4 of this thesis. Additionally, MOVES will provide the emission rates which will be used in the selected dispersion model. This choice is based on the number of studies that also used MOVES and found the emission rates correlated well with the concentrations measured.

3. POPULATION DEMOGRAPHICS OF PORT COMMUNITIES IN GEORGIA, TEXAS AND CALIFORNIA

Drivers often idle for long periods of time outside of port gates, generating high concentrations of pollutants from idling in one area. These operations pose a health risk, because emissions generated by trucks idling at port gates are in addition to emissions from ships, freight handling equipment, and dust. Emissions from these sources put truck drivers, port workers, and neighboring communities at risk for respiratory and cardiovascular disease. Many of the studies discussed in the population exposure studies portion of the literature review in this paper neglect to define the socioeconomic status position (SEP) of participants in their study or vary their definition of this characteristic (Holquin, 2008).

SEP characterization is an important component of the documentation required with any transportation, infrastructure, or commercial project. This characterization is often encompassed in an Environmental Impact Assessment Report for a project as part of the Environmental Justice section. For Environmental Justice reports done as part of a regulatory analysis, the EPA has published criteria defining what constitutes a population group of concern. This definition is based on Executive Order 12898 and identifies the following populations as groups of concern: minority populations, low-income populations, and indigenous peoples (United States Environmental Protection Agency, 2016).

To aid in Environmental Justice analyses, the EPA has a screening tool called EJSCREEN. This screening tool indicates areas that may require further review, but was not intended to be a comprehensive risk assessment tool. The tool cannot be used as a detailed environmental justice analysis tool due to two significant limitations in EJSCREEN: 1.) Because it was created as a national screening tool, it does not capture all local environmental concerns; 2.) The tool uses environmental and demographic data that have associated uncertainties (United States Environmental Protection Agency, June 2016). This data uncertainty in EJSCREEN discourages its use at the block group level and users are cautioned against deriving meaningful information from modest differences between block group data. Combining data from several block groups into a buffer zone is one way to minimize the uncertainty associated with block group level data.

EJSCREEN uses six demographic indicators: percent low-income, percent minority, less than high school education, linguistic isolation, individuals under age 5, and individuals over age 64 (United States Environmental Protection Agency, 2016). The modeling tool provides several indices that combine environmental indicators and demographic information in an effort to quantify the co-occurrence of two different factors. One of these indicators considers only the two characteristics mandated in the Environmental Justice analysis guidance: percent low-income and percent minority, which is referred to as the demographic index

When assessing the vulnerability of a population, it is important to consider more than health indicators and air quality indicators in addition to the population characteristics required by the EPA. Of the characteristics cited for use by the EPA in EJSCREEN, one study found that educational attainment was the most consistent indicator for the vulnerability of a given population (McNeil et al., 2003). This variability in the accuracy of vulnerability characterization parameters recommended for use in Environmental Justice analysis can be a source of confusion for many studies.

Based on the recommendations made by the EPA and the findings of other studies, this research looks at: income, race, housing occupancy, house and family size, age, education, and linguistic isolation to analyze the vulnerability of populations near six selected ports. From these findings, researchers can determine the appropriateness of expanding their study to consider population exposures related to ports.

Mapping demographic indicators for communities surrounding ports was done using ArcGIS to analyze TIGER/Line Shapefiles provided by the US Government Census Bureau (United States Census Bureau, 2015) and using the EJSCREEN geo-database provided by the EPA. The maps generated using this data are presented in the subsequent sub-sections and are organized by demographic indicator with each port mapped separately.

3.1. Population Income

This section looks at the percentage of the population within a census block group that is low income, which is defined as having an income less than two-times the poverty level. The poverty level for 2016, which is the year the income data used came from, is shown in Table 3 as this value varies by family size (United States Department of Human & Health Services, 2016). The income data used for this section was included in the EJSCREEN geodatabase, and was derived from the American Community Survey from the US Census Bureau (United States Environmental Protection Agency, June 2016).

Table 3: 2016 Federal Poverty Level by Household Size

Household Size	2016 Federal Poverty Level
1	$11,880
2	$16,020
3	$20,160
4	$24,300
5	$28,440
6	$32,580
7	$36,730
8	$40,890

The ports in this section are indicated by the red symbol of a ship shown in Figure 1. Some of the ports are shown as being inland and not located directly on the coast. These ports a series of rivers and channels ,which are not shown on the map, connects these ports. The river network connecting the ports is most extensive for the Port of Houston, and some locations of the port are more than 30-kilometers inland for several locations.

Figure 1: Icon used to indicate where a port is located on the population demographic maps

Figure 2 shows the percentages of low income populations for census block groups in Los Angeles, California with locations for the Ports of Long Beach and Ports of Los Angeles indicated in red.

Figure 3 shows the percentages of low income populations for census block groups in Houston, Texas with locations for the Port of Houston indicated in red.

Figure 4 shows the percentages of low income populations for census block groups in Brunswick, GA with locations for the Port of Brunswick indicated in red.

Figure 5 shows the percentages of low income populations for census block groups in Savannah, GA with locations for the Port of Savannah indicated in red.

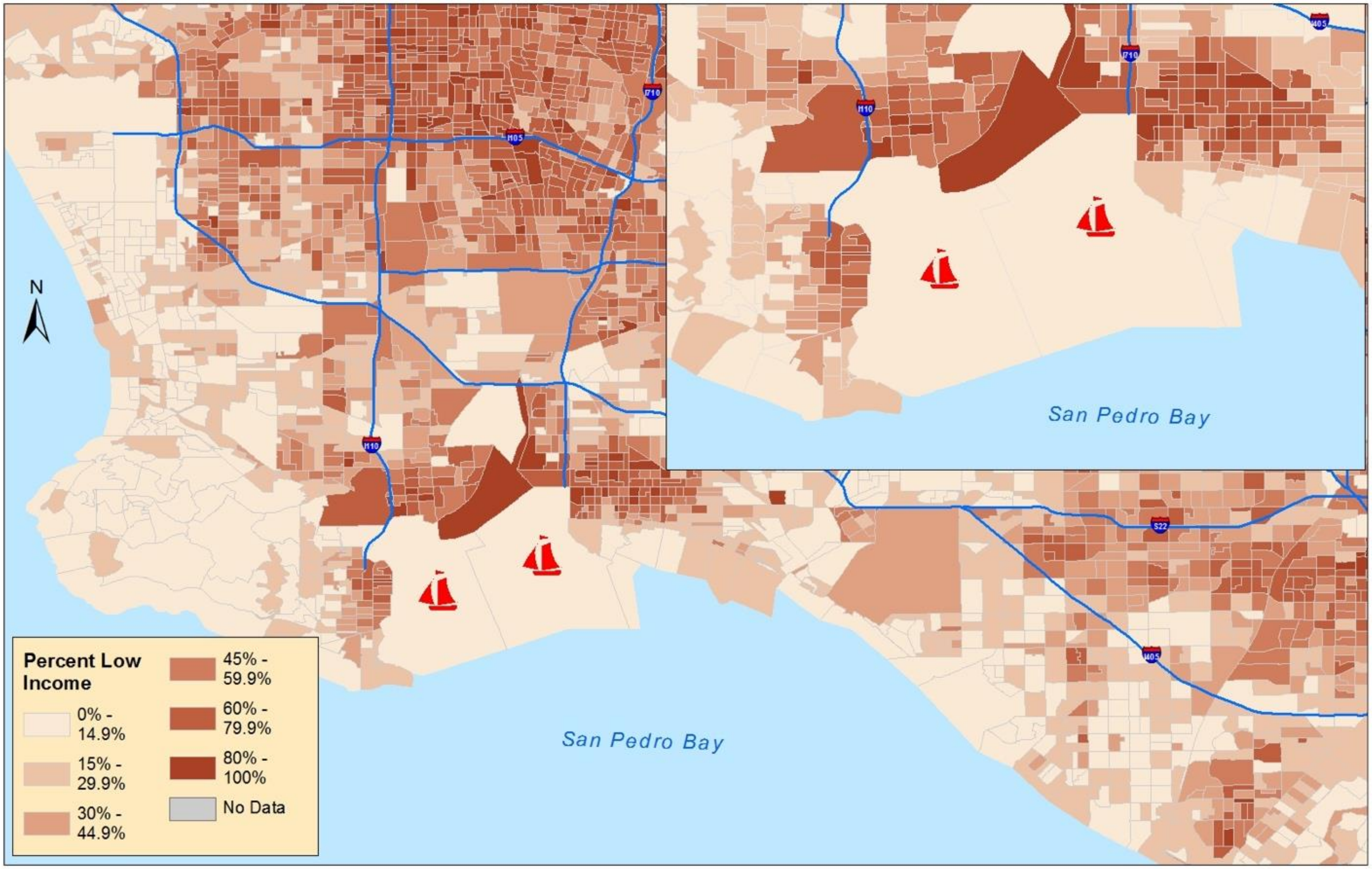


Figure 2: Percentages of low income populations surrounding the Ports of Los Angeles and Long Beach

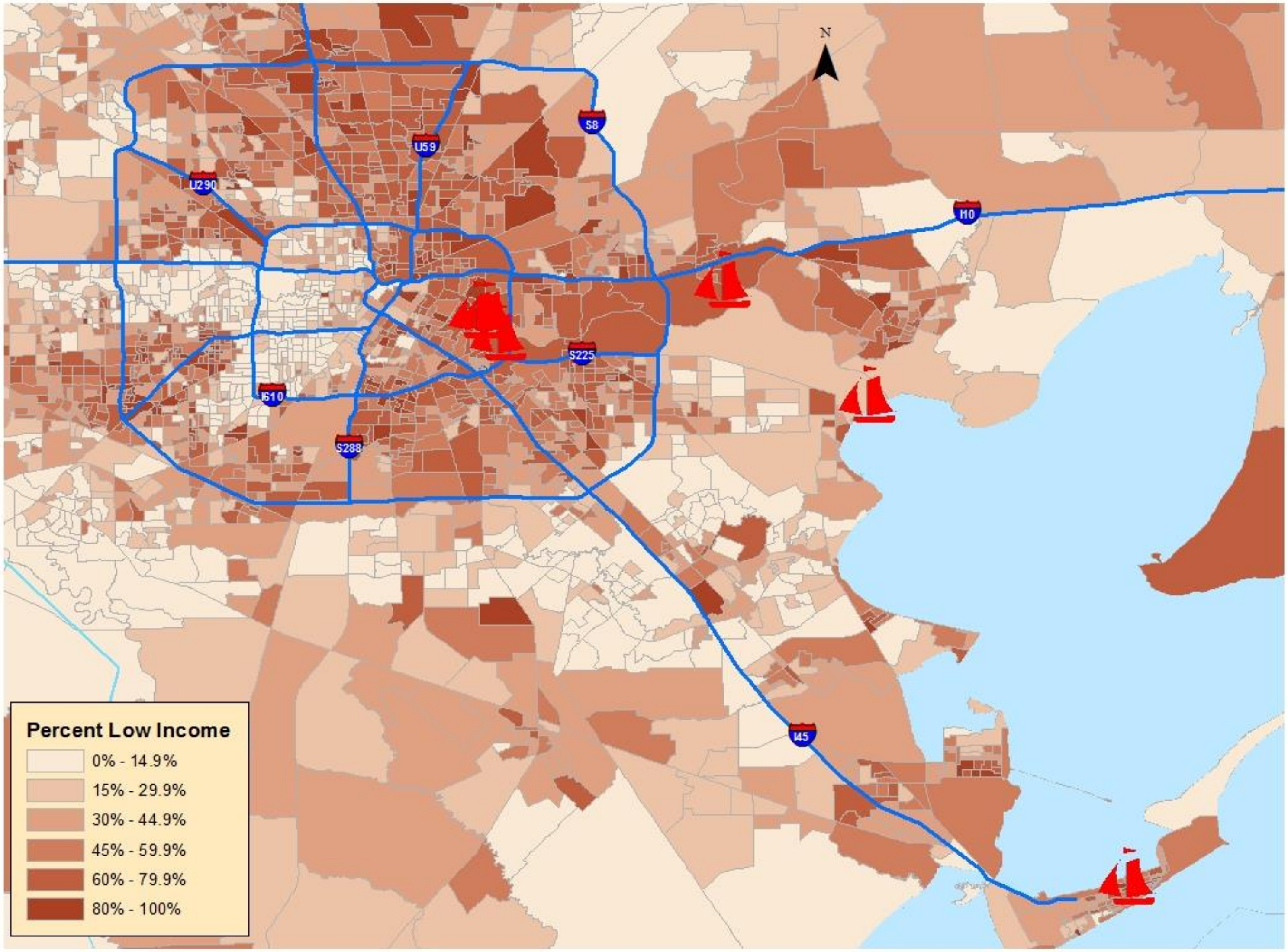


Figure 3: Percentages of low income populations surrounding the Port of Houston

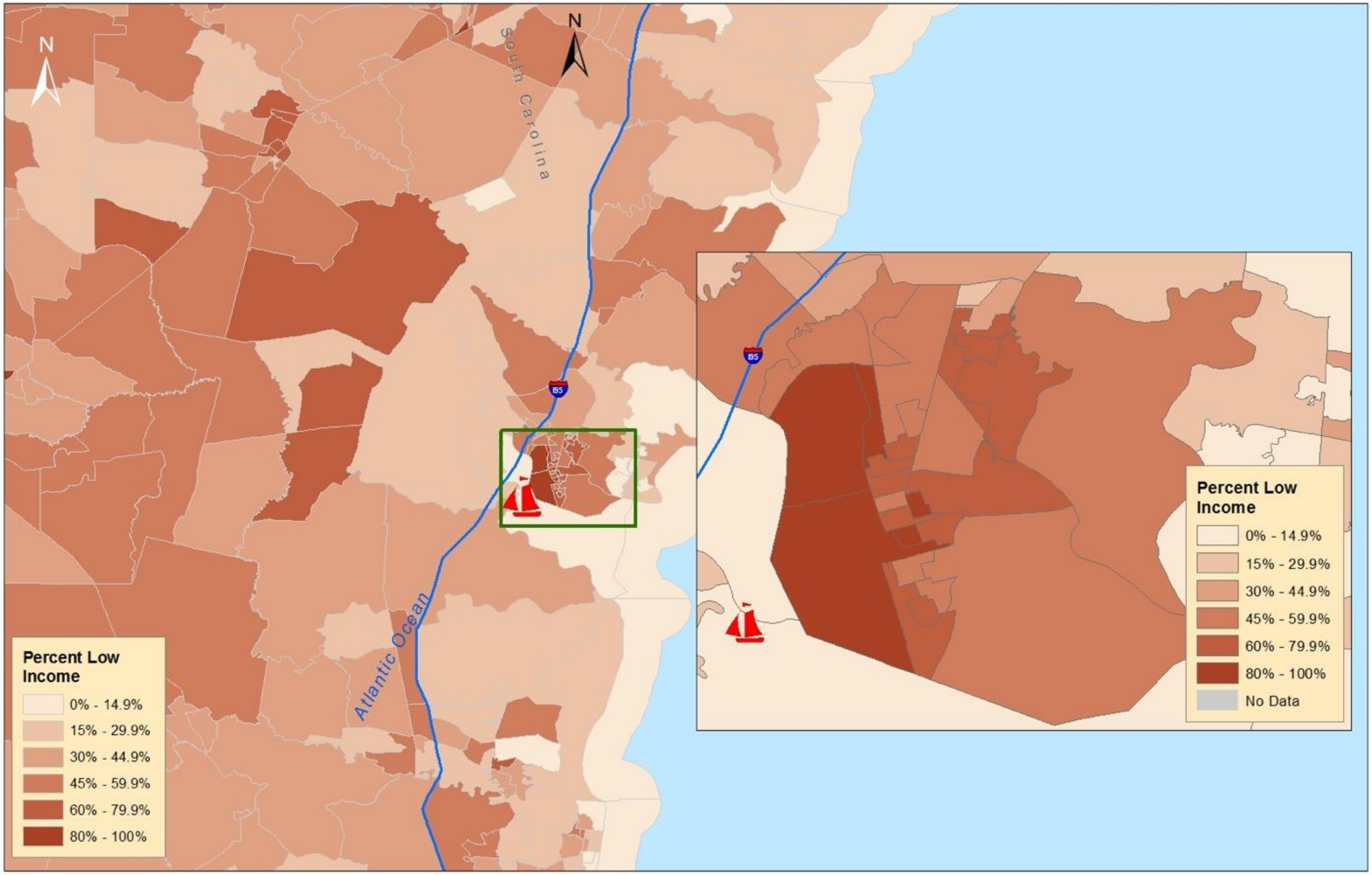


Figure 4: Percentages of low income populations surrounding the Port of Brunswick

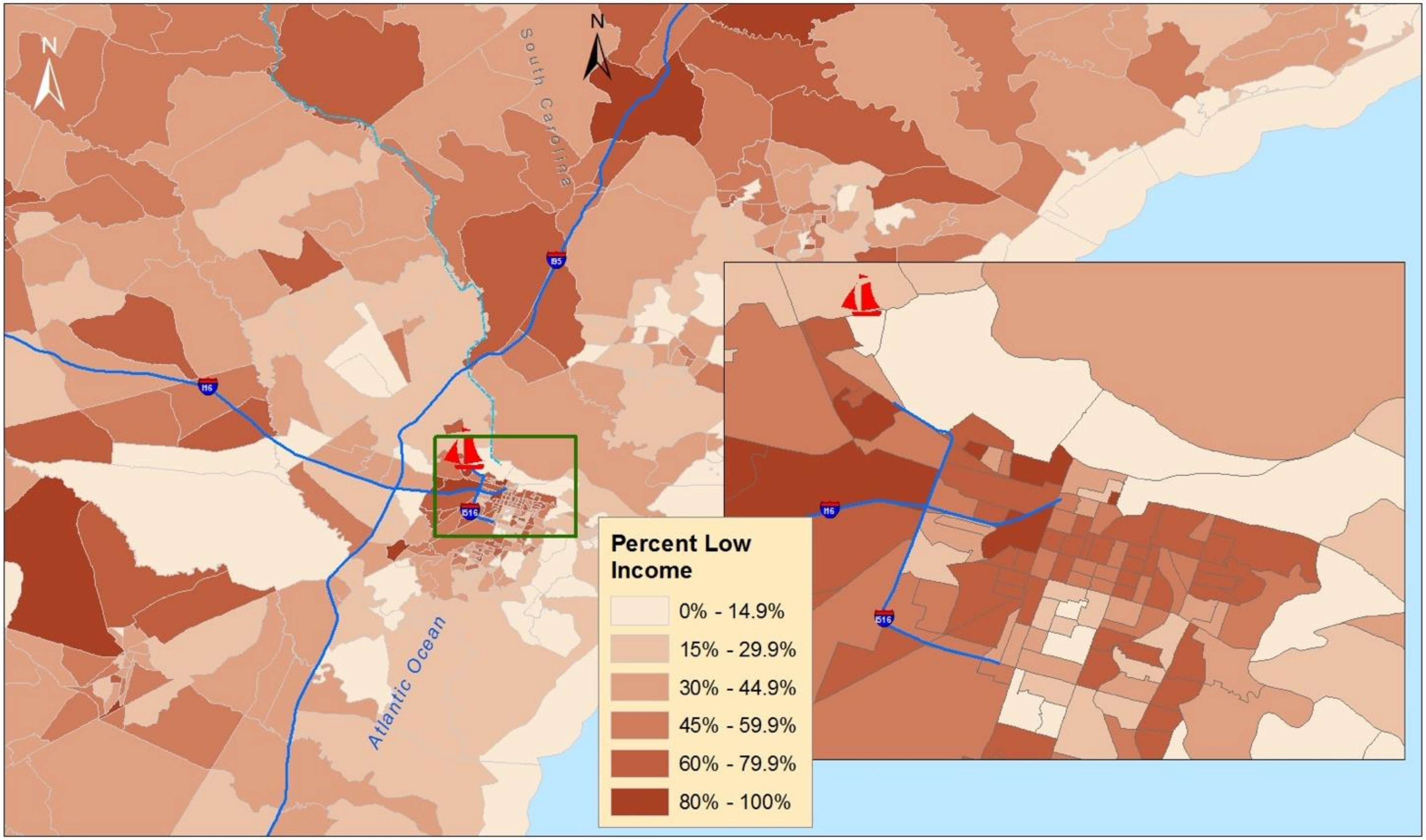


Figure 5: Percentages of low income populations surrounding the Port of Savannah

3.2. Population Racial Make-up

This section looks at the racial makeup of the census tract areas surrounding each port. Racial makeup is presented by mapping the spatial variability of minority populations surrounding each port. Minority populations are comprised of any individual's whose racial status is not white alone nor Hispanic or Latino. White-alone populations are defined as those people that reported their race as white not in combination with some other race. The EPA's EJSCREEN tool provides the data used to create the figures in this section.

Figure 8 shows the percentages of minority populations for census block groups in Los Angeles, California with locations for the Ports of Long Beach and Ports of Los Angeles indicated in red.

Figure 7 shows the percentages of minority populations for census block groups in Houston, Texas with the different locations for the Port of Houston indicated in red.

Figure 8 shows the percentages of minority populations for census block groups in Brunswick, Georgia with the location of the Port of Brunswick indicated in red.

Figure 9 shows the percentages of minority populations for census block groups in Savannah, Georgia with the location of the Port of Savannah indicated in red.

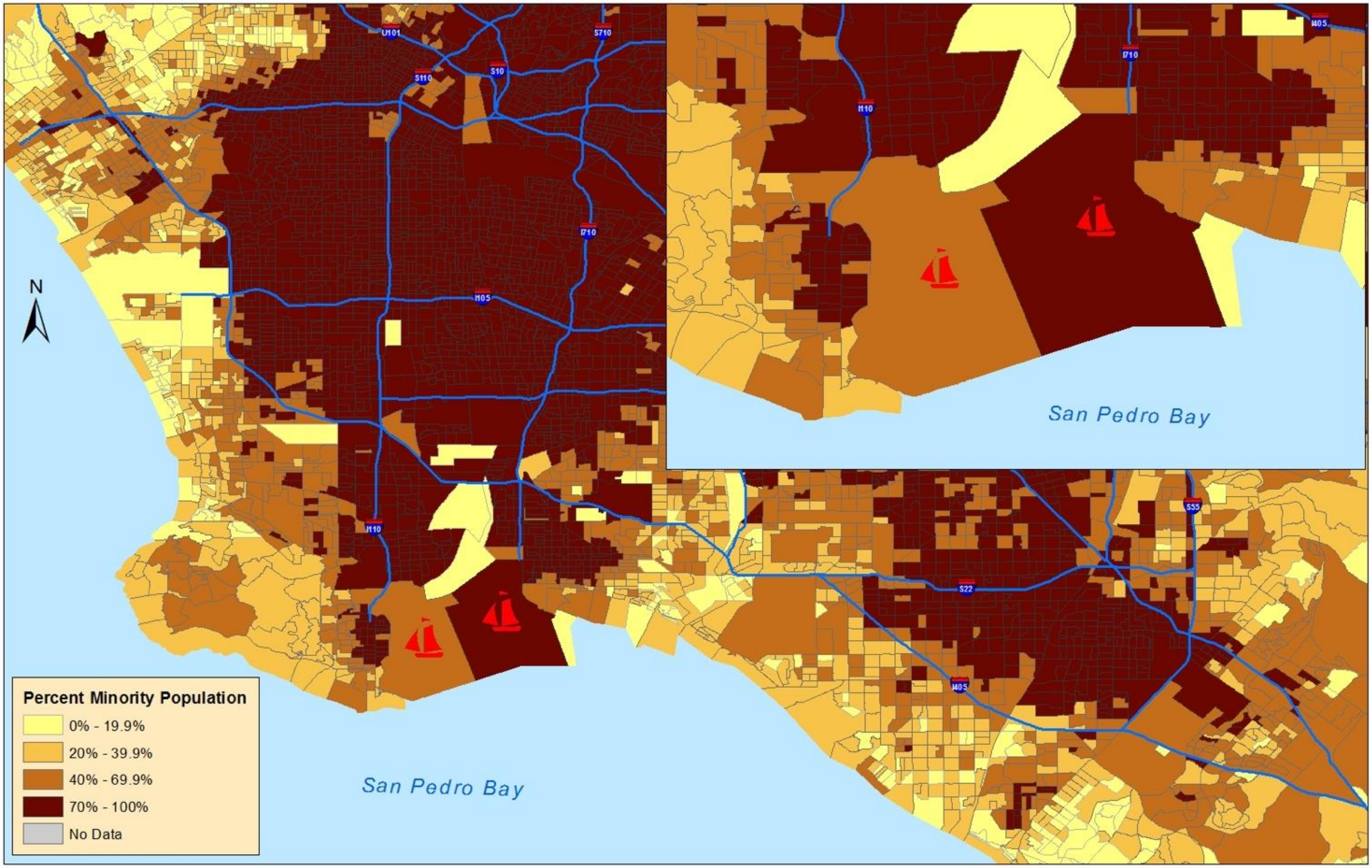


Figure 6: Percentages of minority populations surrounding the Port of Los Angeles and Port of Long Beach

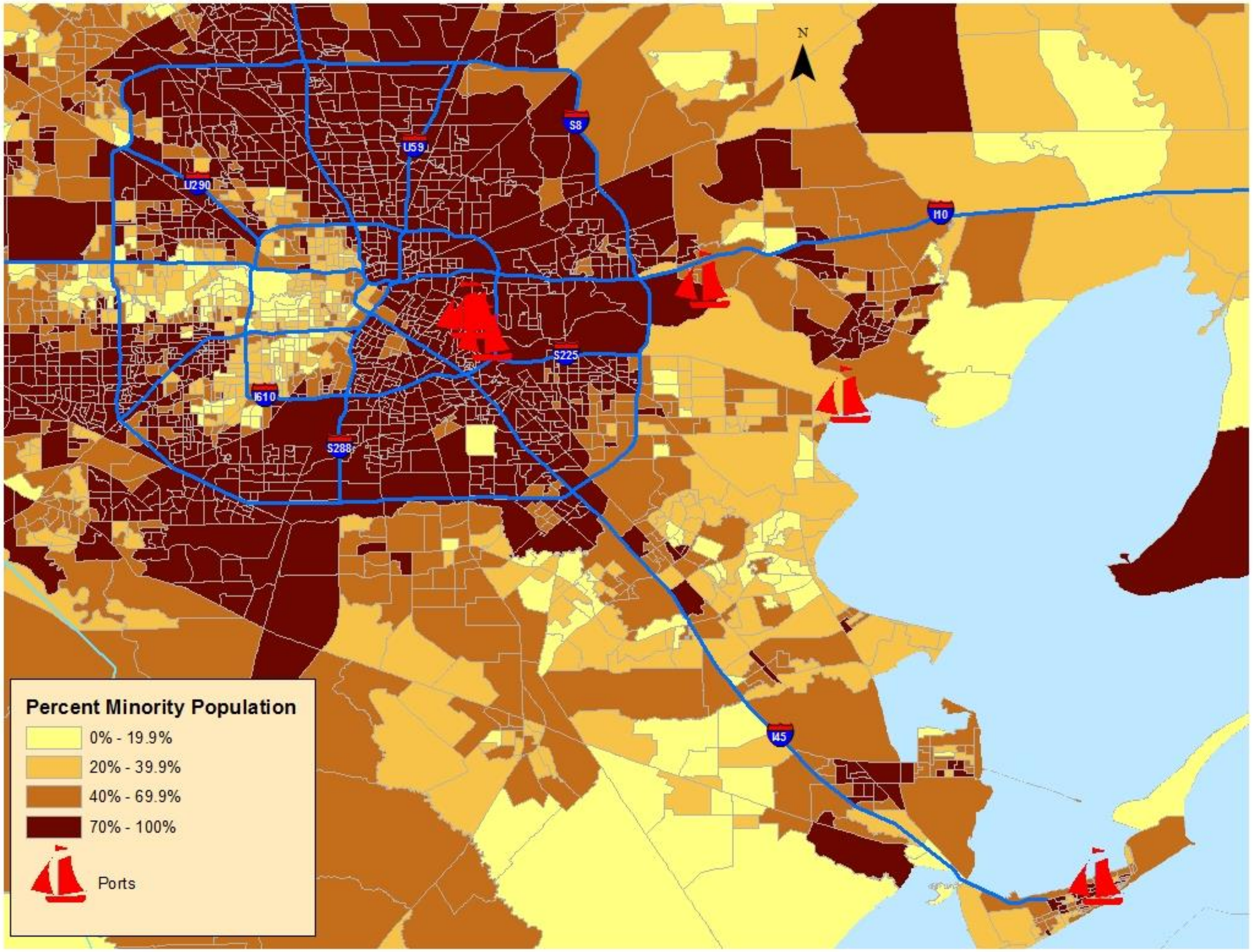


Figure 7: Percentages of minority populations surrounding the Port of Houston

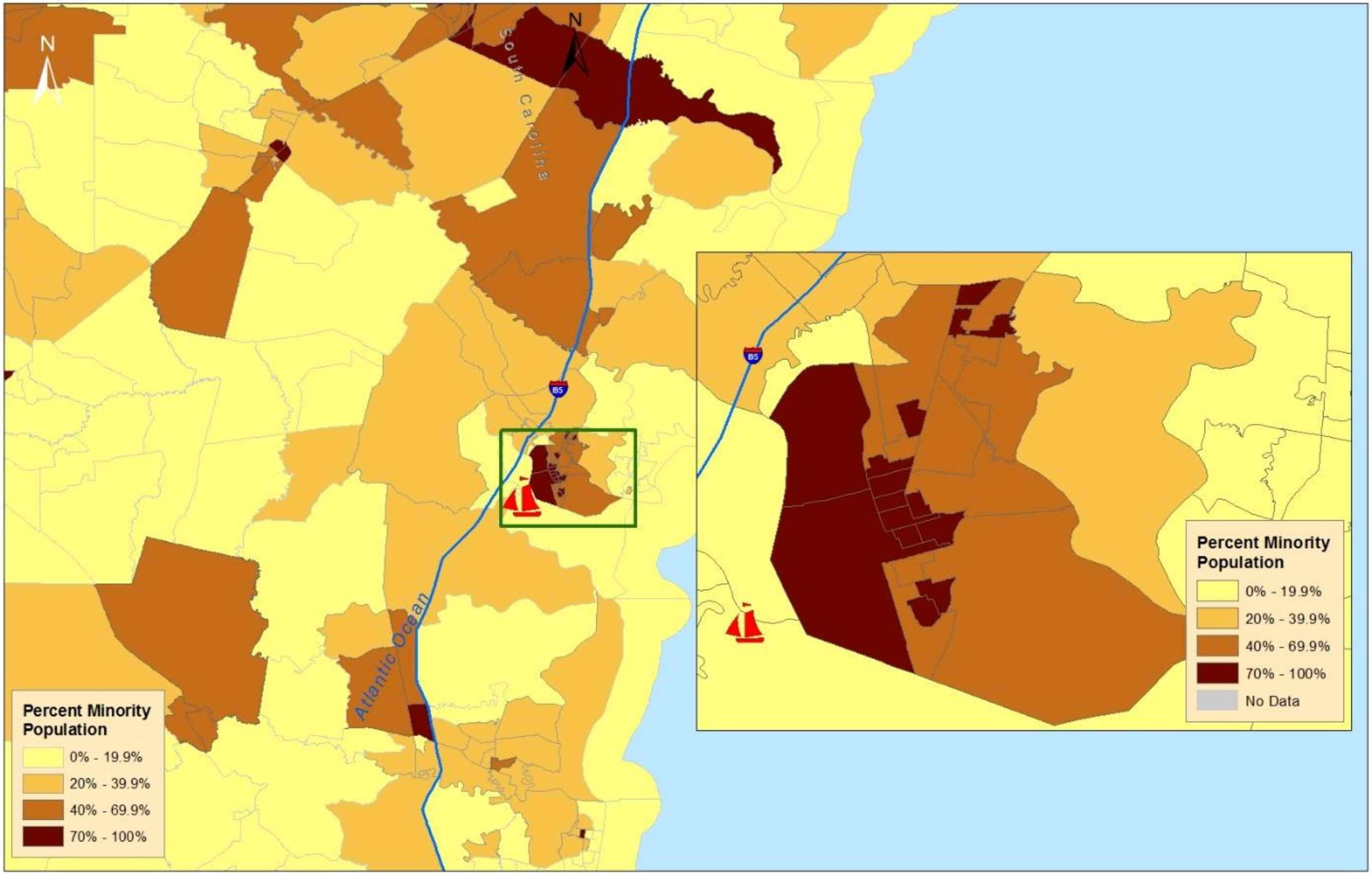


Figure 8: Percentages of minority populations surrounding the Port of Brunswick

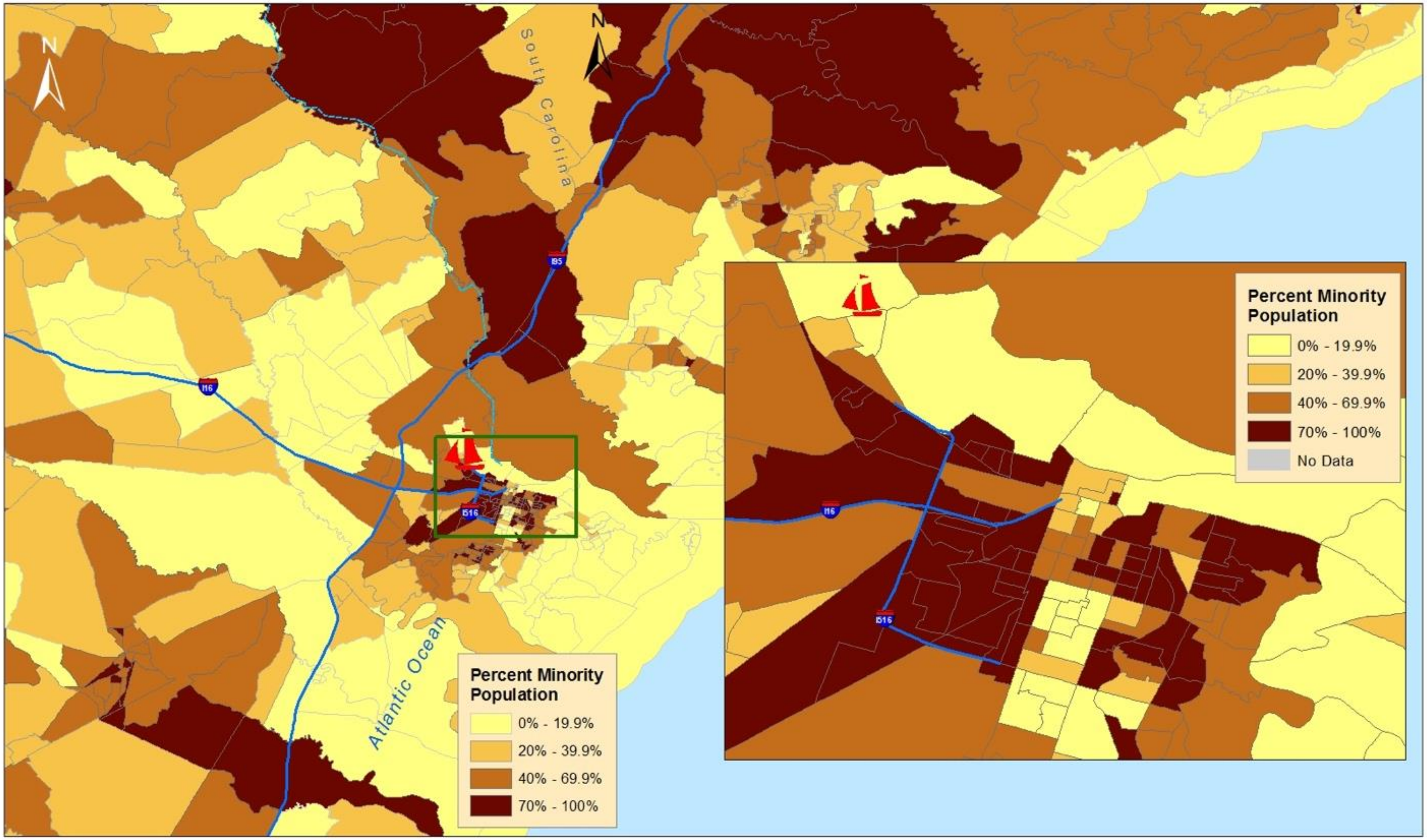


Figure 9: Percentages of minority populations surrounding the Port of Savannah

3.3. Housing Occupancy

This section looks at the number of vacant housing units as a ratio of the total housing units. The information presented in the maps is presented as three subplots for each port/state. The subplots are presented in the same format and present the same information for each state. The information presented in each map includes: housing vacancy rate as a percentage (sub-plot A), owner-occupied household size (sub-plot B), and renter-occupied household size (sub-plot C).

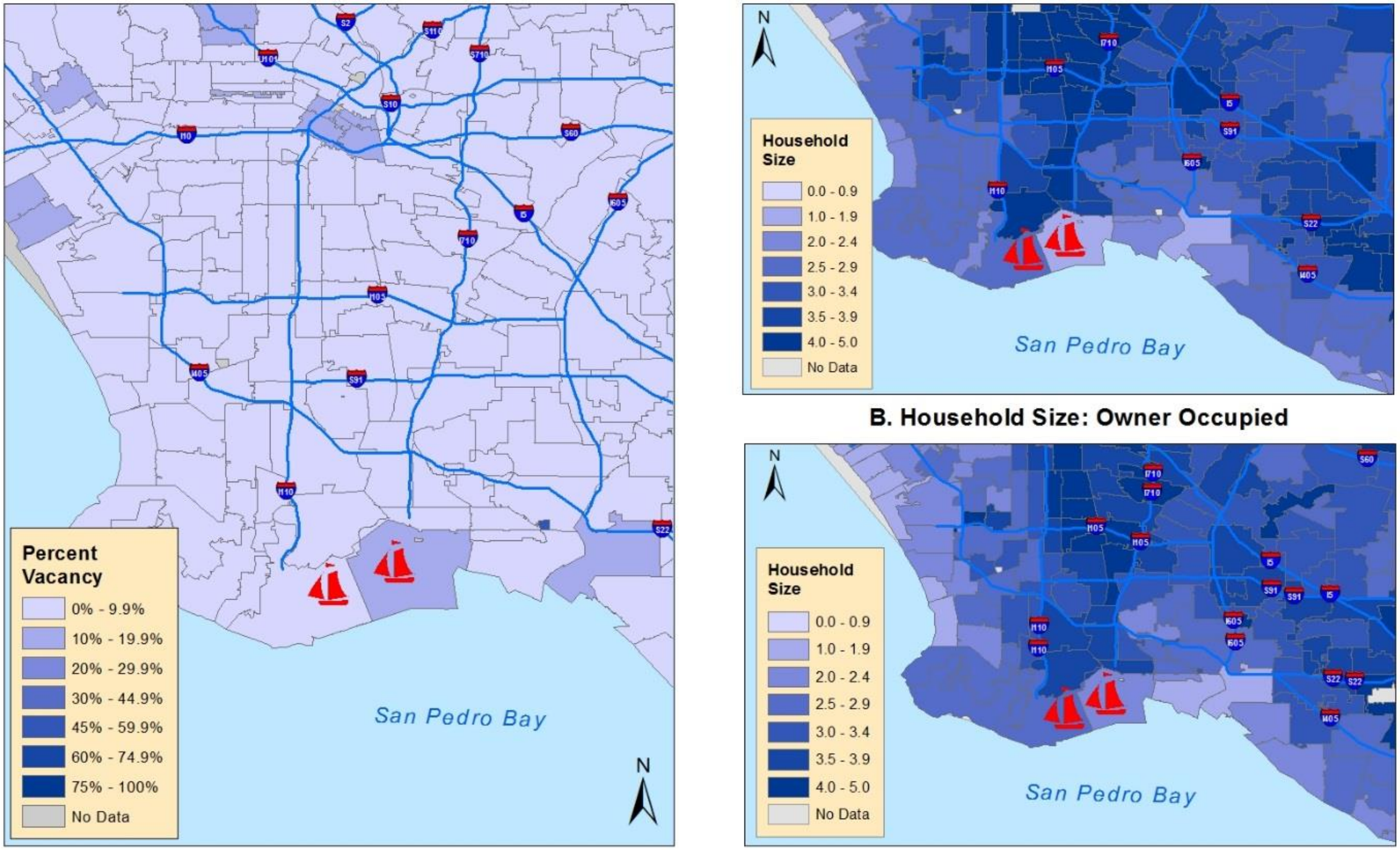
Using housing occupancy as a proxy for socioeconomic status, was done by Smargiassi et al. in a study relating socioeconomic status, respiratory disease, and living near high traffic roadways (Smargiassi, 2006). The results from this study suggest that socioeconomic status is a confounding factor for respiratory disease in the elderly populations studied, as those in lower socioeconomic classes reside disproportionately near high traffic roadways. The study did show that residing near high traffic areas had the most significant effect on the odds of being hospitalized for respiratory disease. The results of this study suggest that future spatial analysis should include traffic volumes in addition to census data for income and housing occupancy. In future efforts, multivariate logistic regression could be used to incorporate the effects of these confounding factors on a person’s exposure to pollutants associated with diesel exhaust.

Figure 10 shows the household occupancy demographics for the census block groups in Los Angeles, California with the locations of the Port of Los Angeles and Port of Long Beach with the port indicated in red.

Figure 11 shows the household occupancy demographics for the census block groups in Houston, Texas with the locations of the Port of Houston indicated in red.

Figure 12 shows the household occupancy demographics for the census block groups in Brunswick, Georgia with the location of the Port of Brunswick indicated in red.

Figure 13 shows the household occupancy demographics for the census block groups in Savannah, Georgia with the location of the Port of Savannah indicated in red.

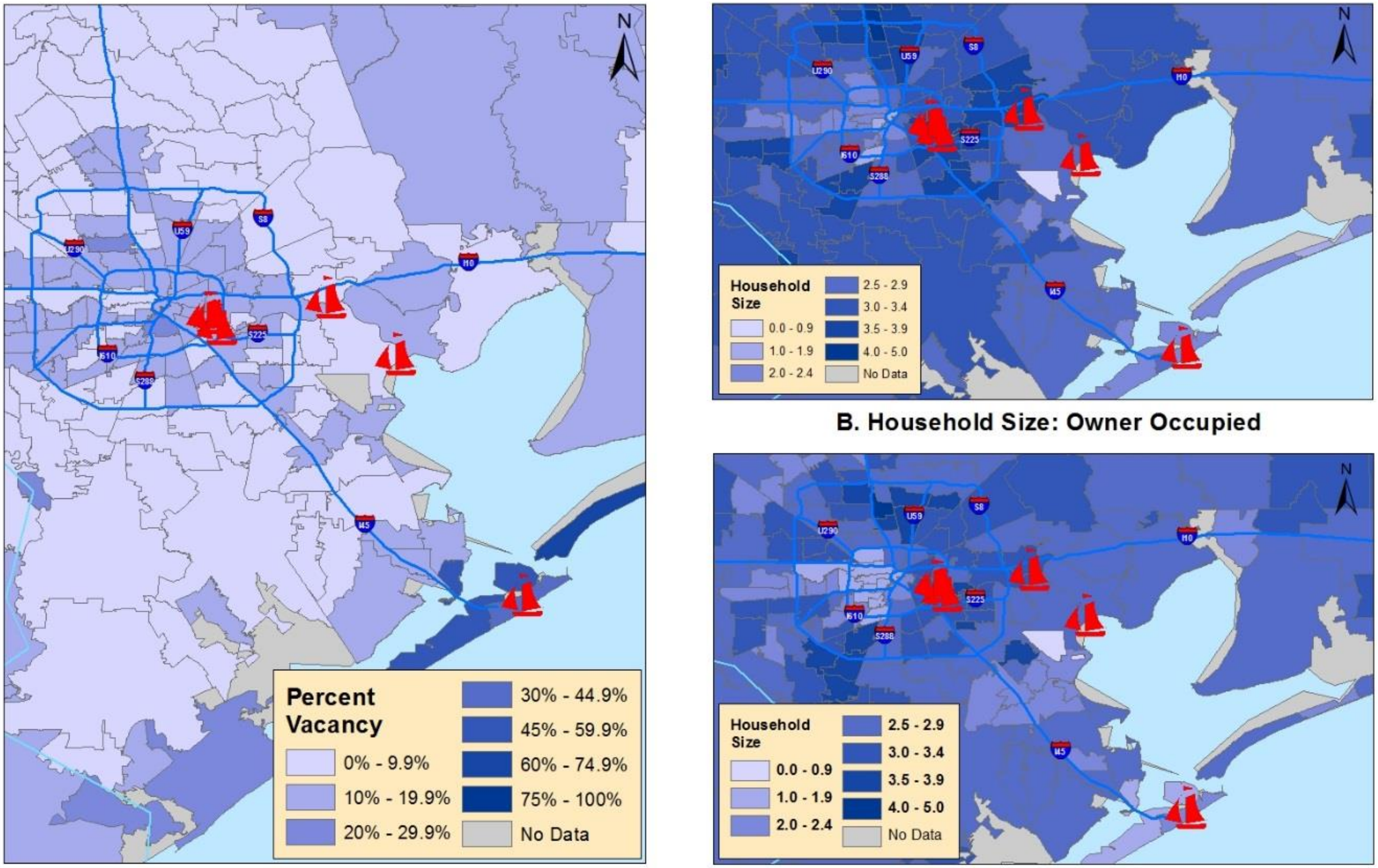


B. Household Size: Owner Occupied

A. Housing Vacancy

C. Household Size: Renter Occupied

Figure 10: Percent vacancy, and renter and owner household size for populations surrounding the Port of Los Angeles and Port of Long Beach



A. Housing Vacancy

C. Household Size: Renter Occupied

Figure 11: Percent vacancy, and renter and owner household size for populations surrounding the Port of Houston

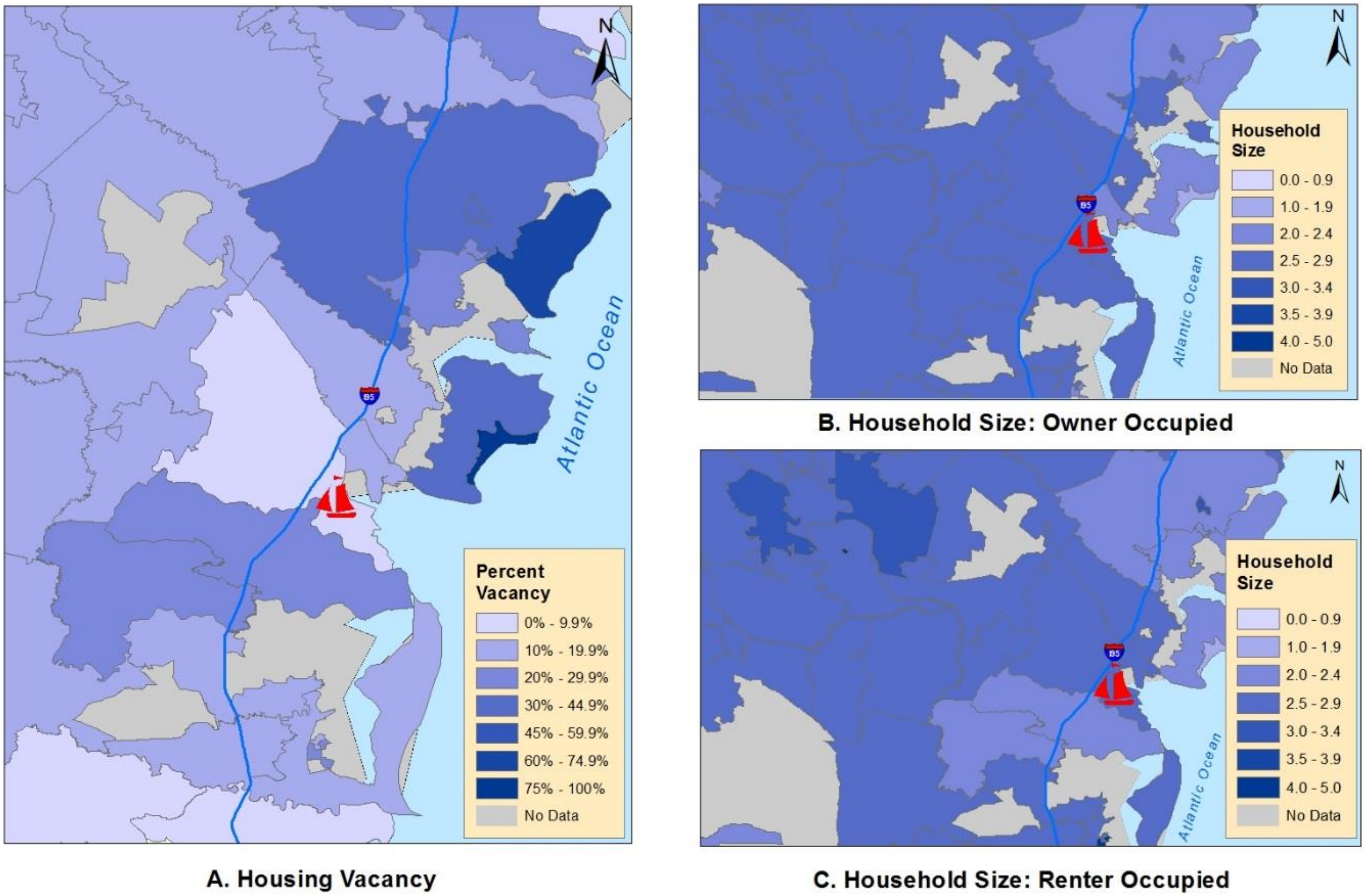
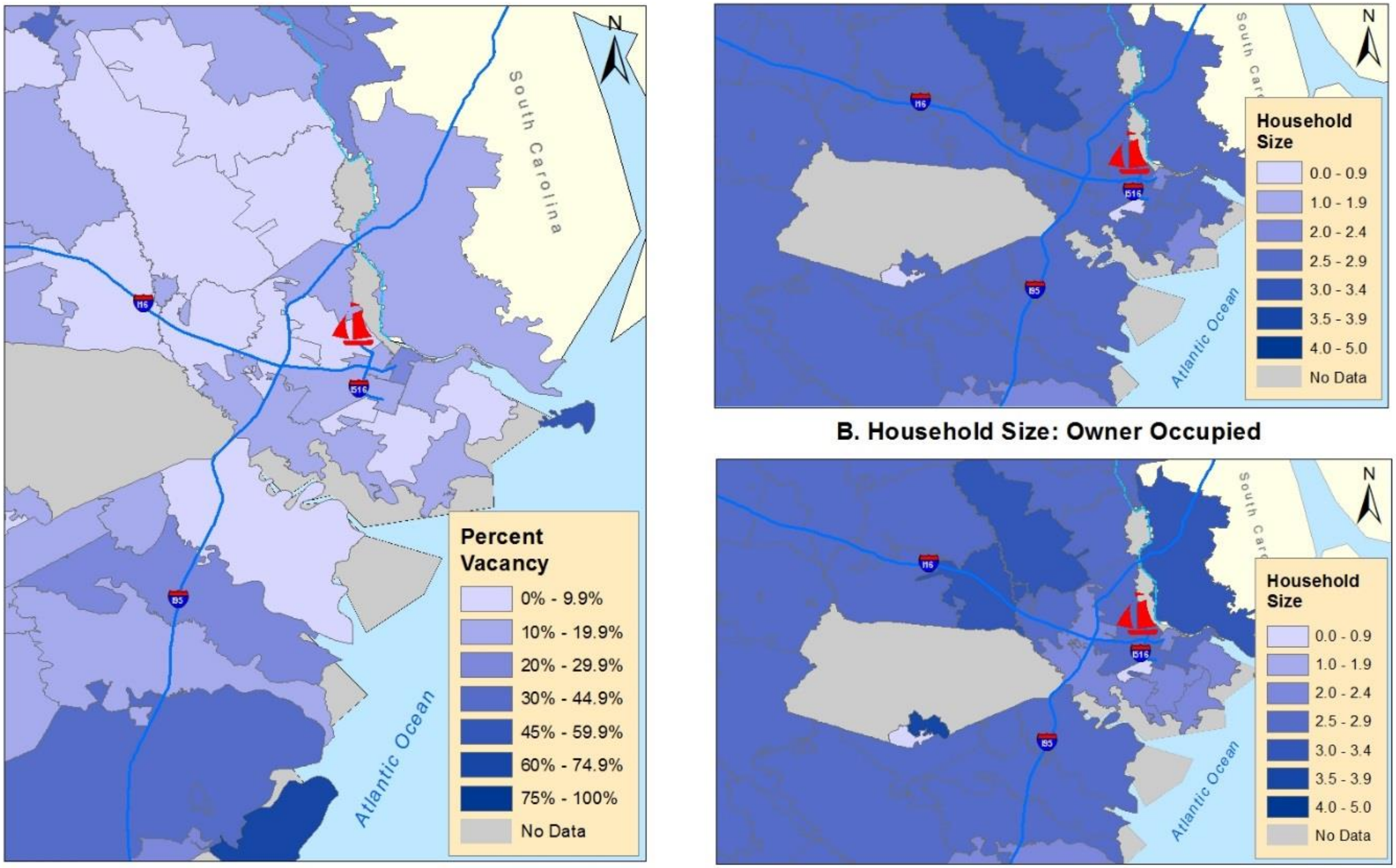


Figure 12: Percent vacancy, and renter and owner household size for populations surrounding the Port of Brunswick



A. Housing Vacancy

B. Household Size: Owner Occupied

C. Household Size: Renter Occupied

Figure 13: Percent vacancy, and renter and owner household size for populations surrounding the Port of Savannah

3.4. House and Family Size

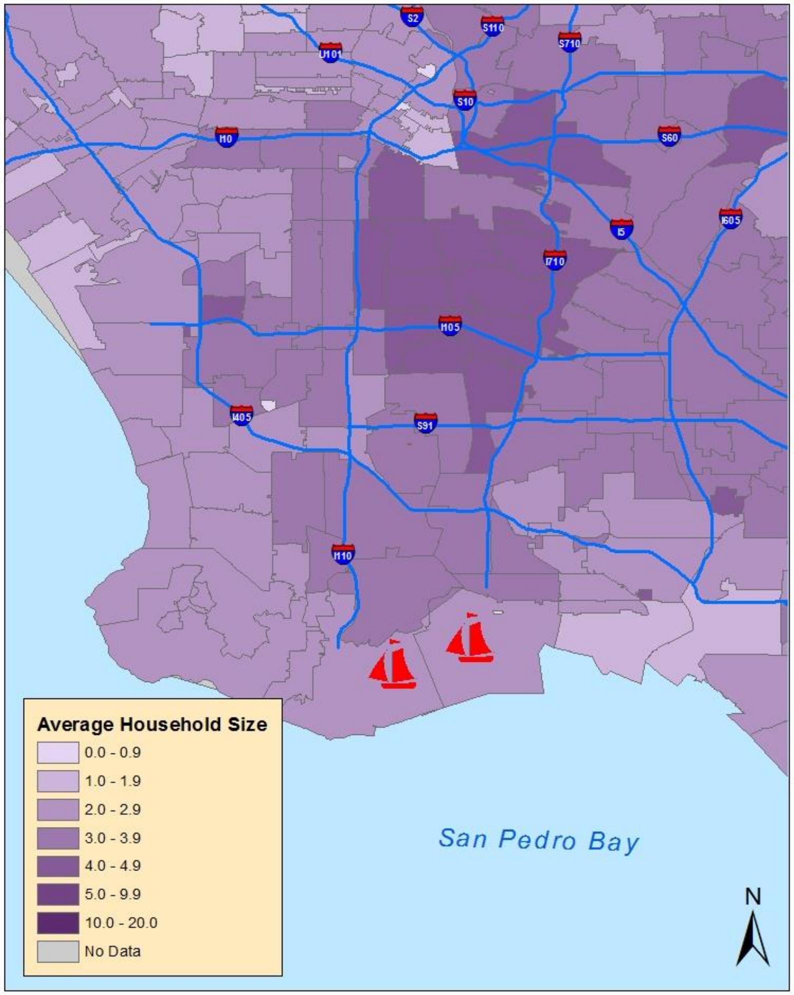
Household size, family size and householder status can be important socio-economic indicators. The information presented in the maps in this section are presented as three subplots for each port/state. The subplots are presented in the same format and present the same information for each state. The information presented in each map includes: average household size (sub-plot A), percent of single householders (sub-plot B), and average family size (sub-plot C). The data used to generate these figures comes from the U.S. Census Bureau.

Figure 14 shows the household demographics for the census block groups in Los Angeles, California with the locations of the Port of Los Angeles and Port of Long Beach.

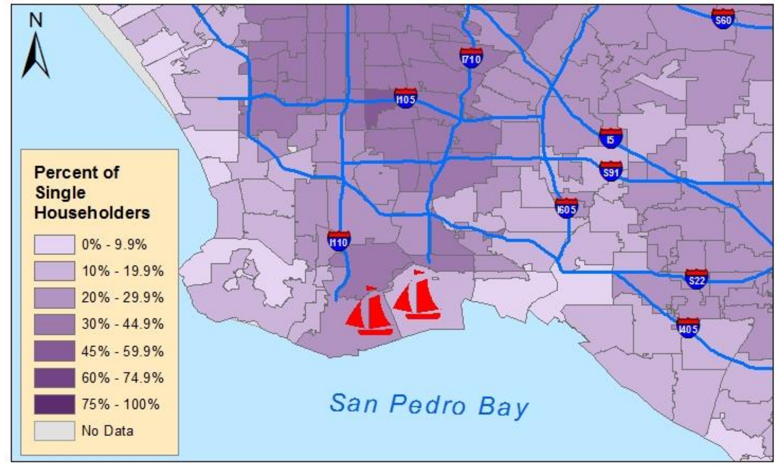
Figure 15 shows the household demographics for the census block groups in Houston, Texas with the different locations of the Port of Houston.

Figure 16 shows the household demographics for the census block groups in Brunswick, Georgia with the different locations of the Port of Brunswick.

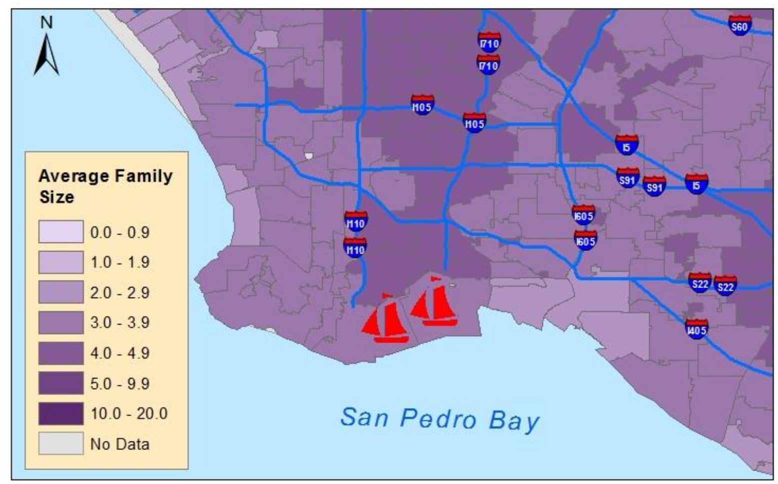
Figure 17 shows the household demographics for the census block groups in Savannah, Georgia with the different locations of the Port of Savannah.



A. Average Household Size

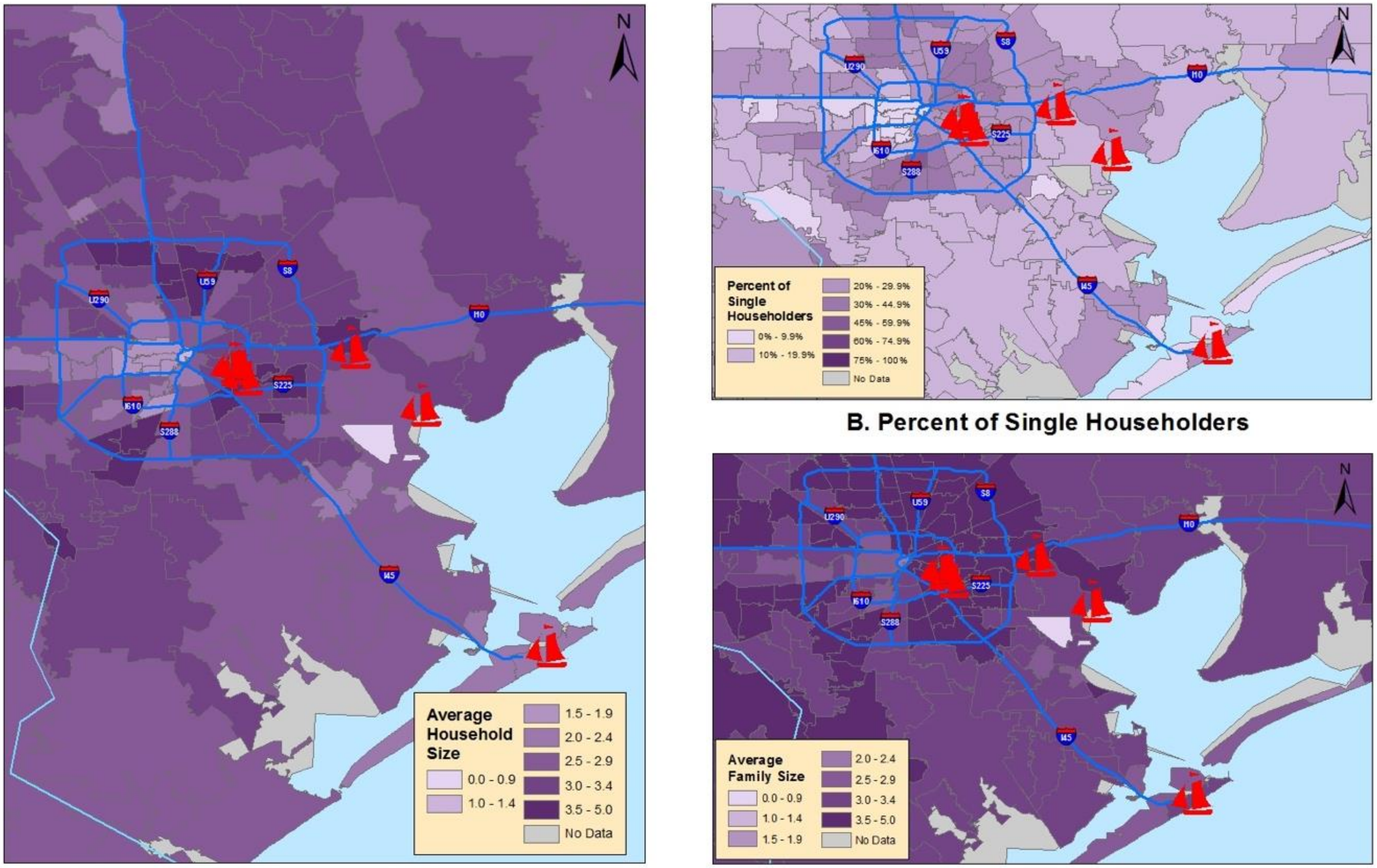


B. Percent of Single Householders



C.Average Family Size

Figure 14: Average household size, family size and single household populations surrounding the Port of Los Angeles and Port of Long Beach



B. Percent of Single Householders

A. Average Household Size

C. Average Family Size

Figure 15: Average household size, family size and single household populations surrounding the Port of Houston

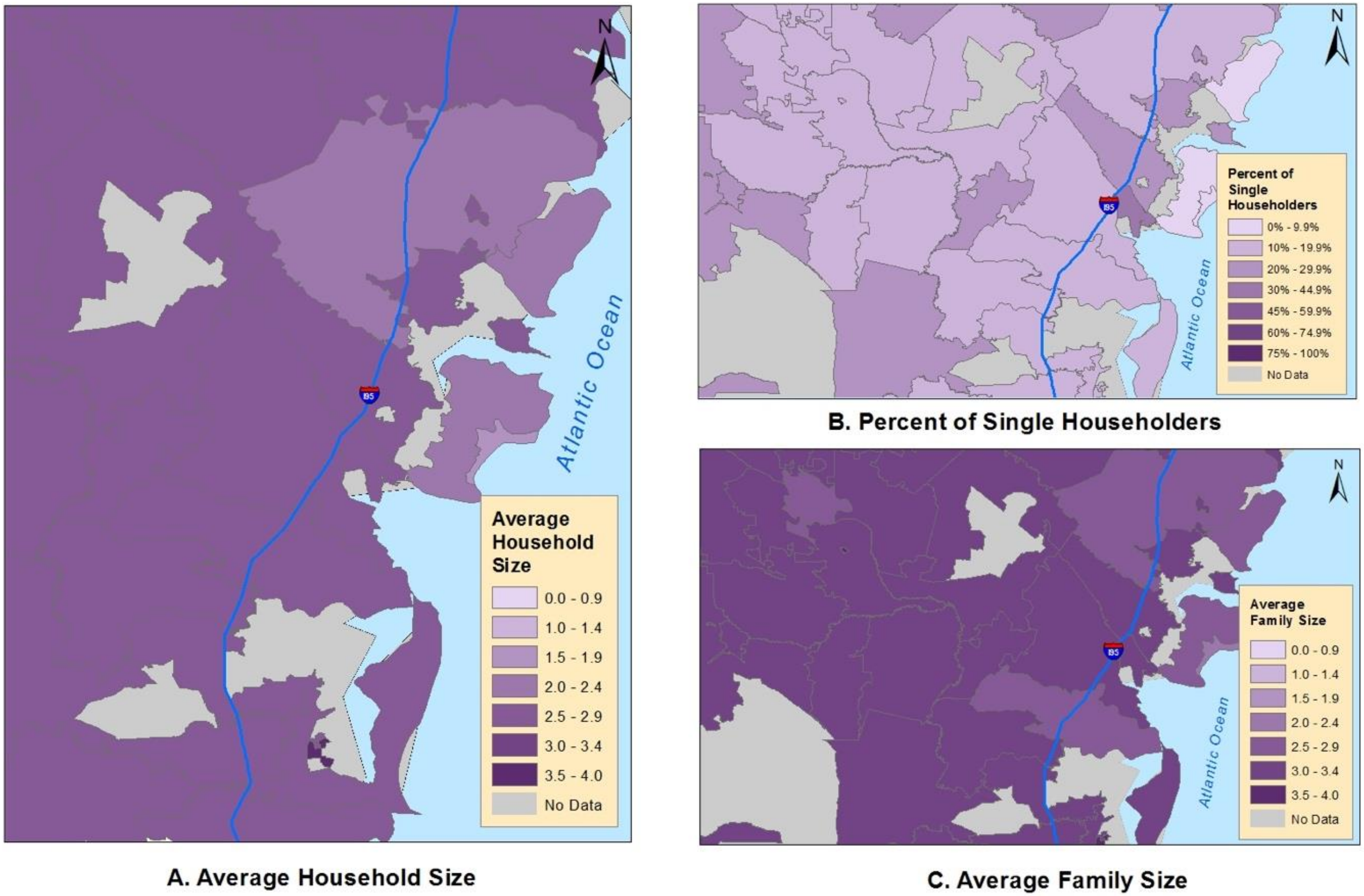
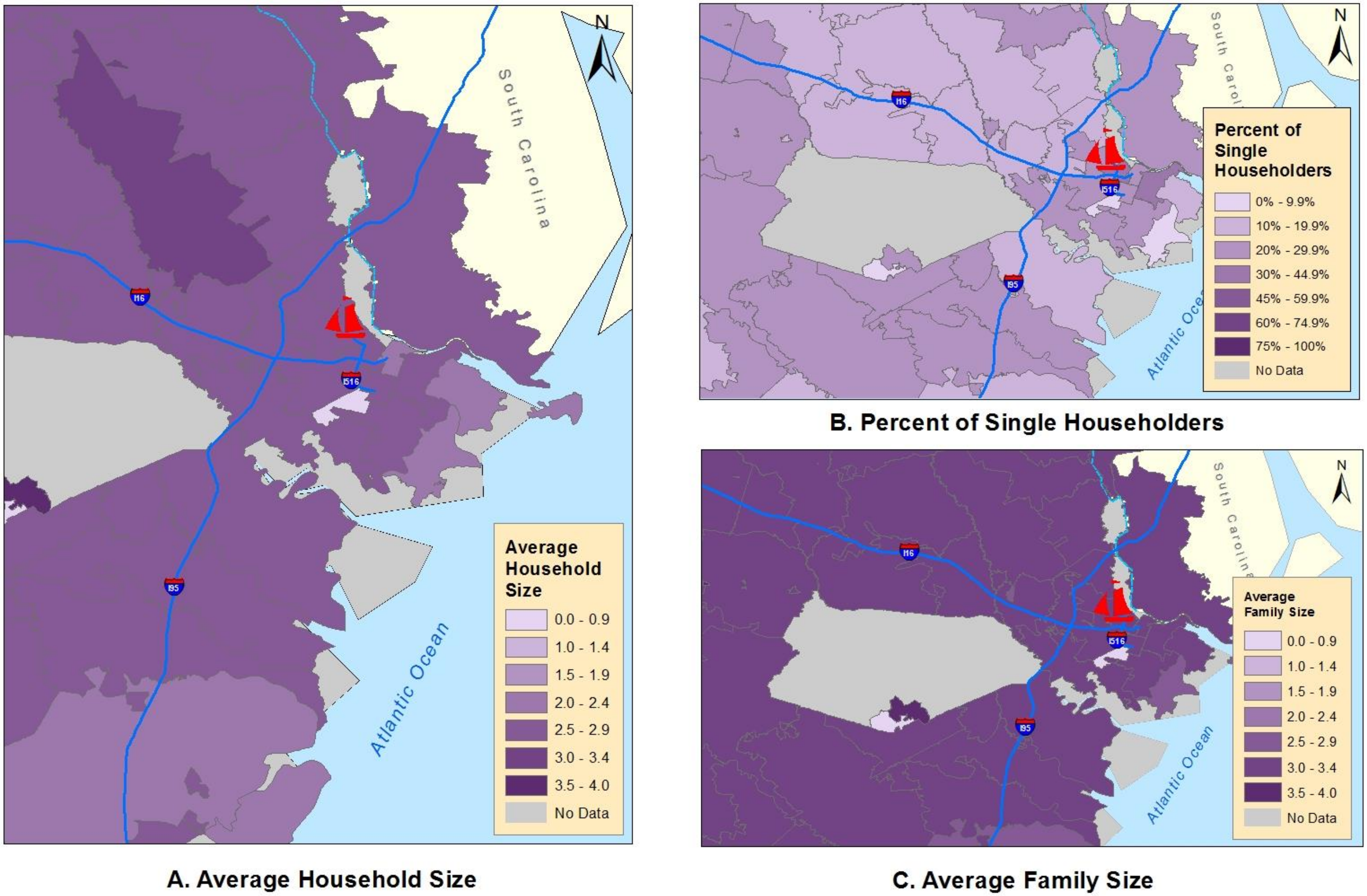


Figure 16: Average household size, family size and single household populations surrounding the Port of Brunswick



A. Average Household Size

B. Percent of Single Householders

C. Average Family Size

Figure 17: Average household size, family size and single household populations surrounding the Port of Savannah

3.5. Age

In the context of age, the EPA describes vulnerable populations as people under age 5 and over age 65. People who fall in either of these categories are known to be more vulnerable to environmental pollutants due to weakened or immature respiratory and cardiovascular systems. The figures presented in this section of the report were created using information provided by the U.S. Census Bureau and include further subdivisions of the age demographics of each study area. The information presented in the maps is presented as three subplots for each port/state. The subplots present the spatial variation in the location of vulnerable populations from both age groups and from each age group individually. The information presented in each map for age-related spatial variation includes: percent of the population under age 5 or over age 65 (sub-plot A), percent of population under age 5 (sub-plot B), and percent of the population over age 65 (sub-plot C).

Figure 18 shows the population demographics for age in the communities surrounding the Port of Los Angeles and Port of Long Beach.

Figure 19 shows the population demographics for age in the communities surrounding the Port of Houston

Figure 20 shows the population demographics for age in the communities surrounding the Port of Brunswick.

Figure 21 shows the population demographics for age in the communities surrounding the Port of Savannah.

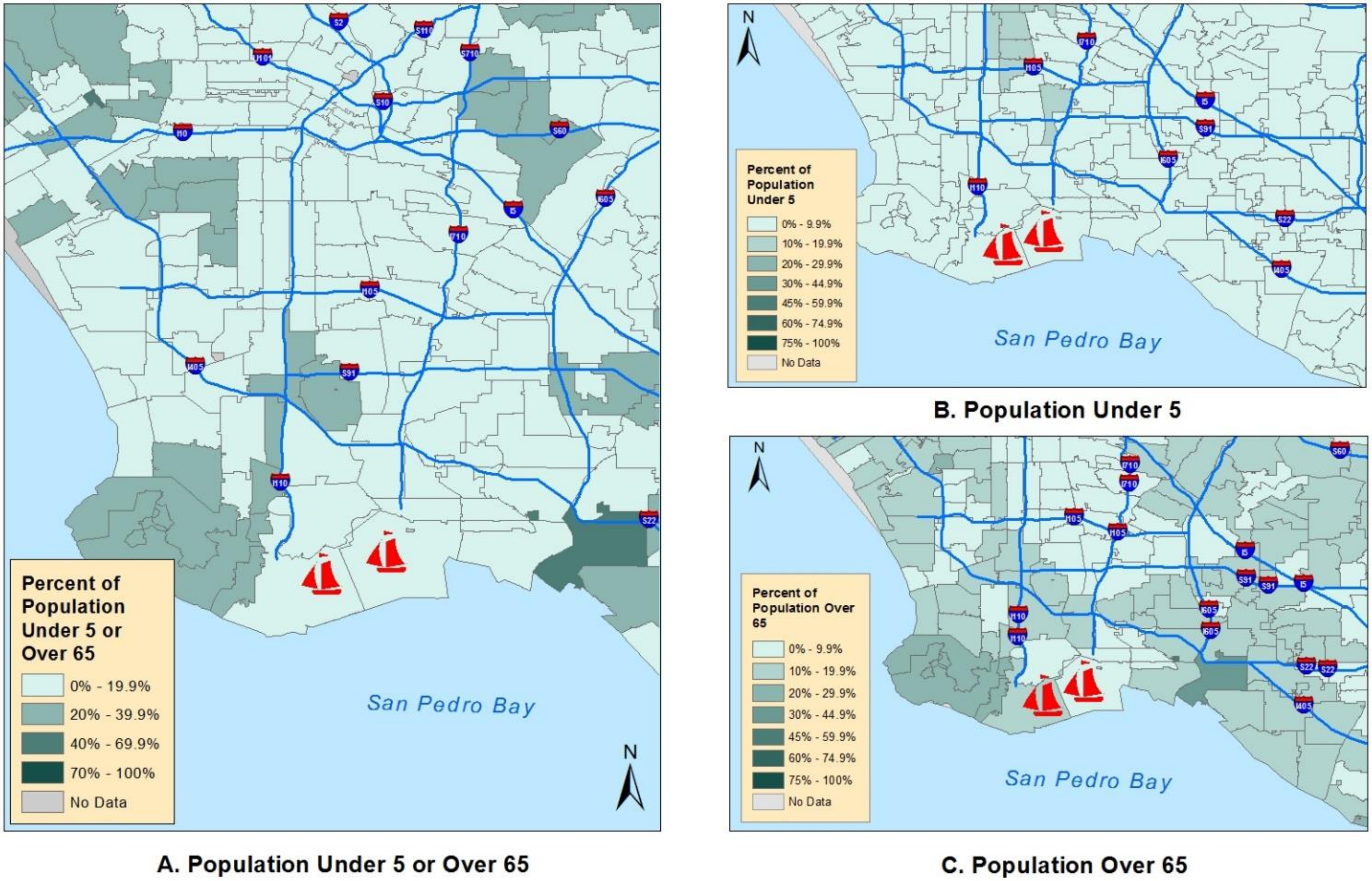
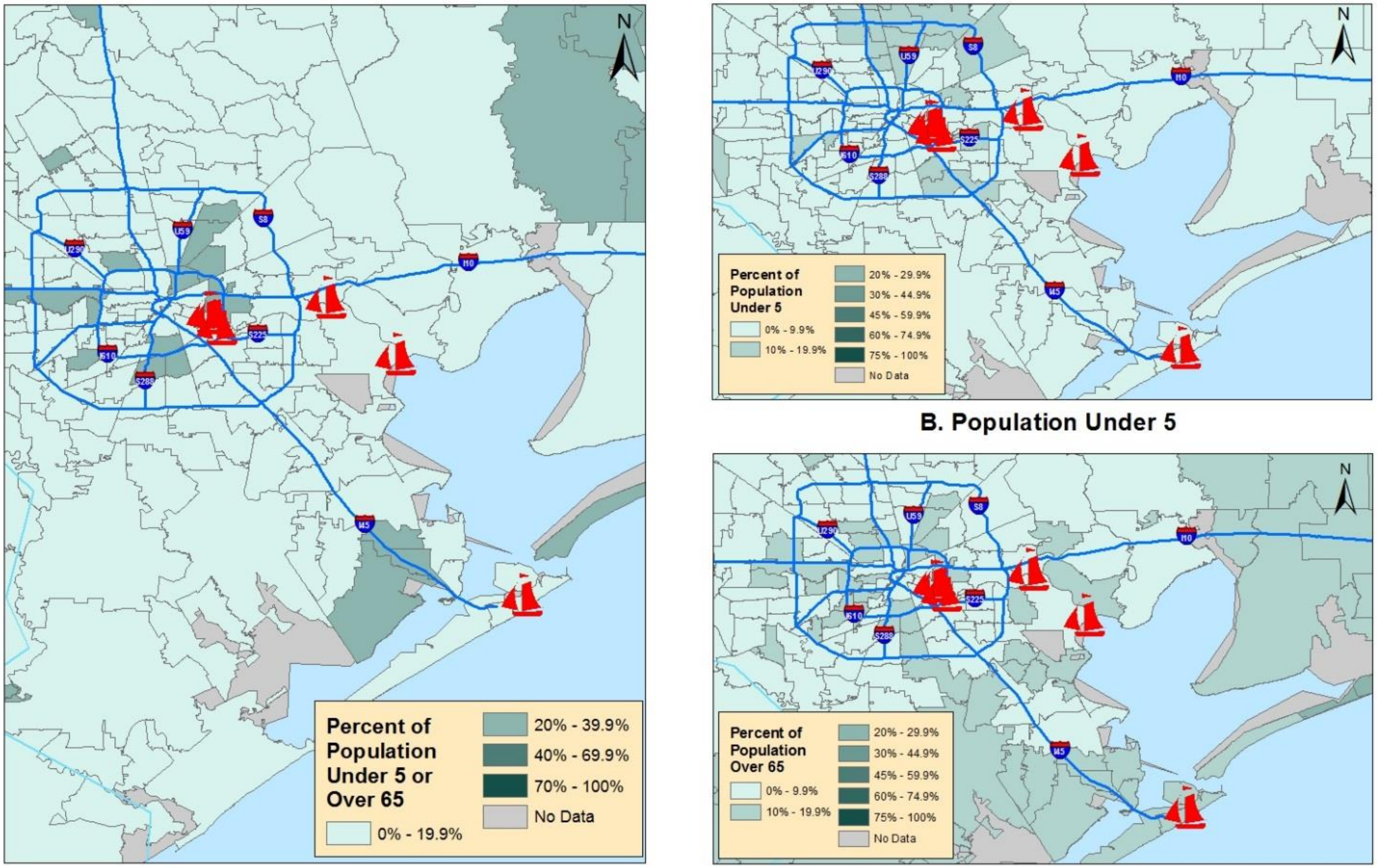


Figure 18: Population demographics for age in census block grounds surrounding the Ports of Los Angeles and Long Beach

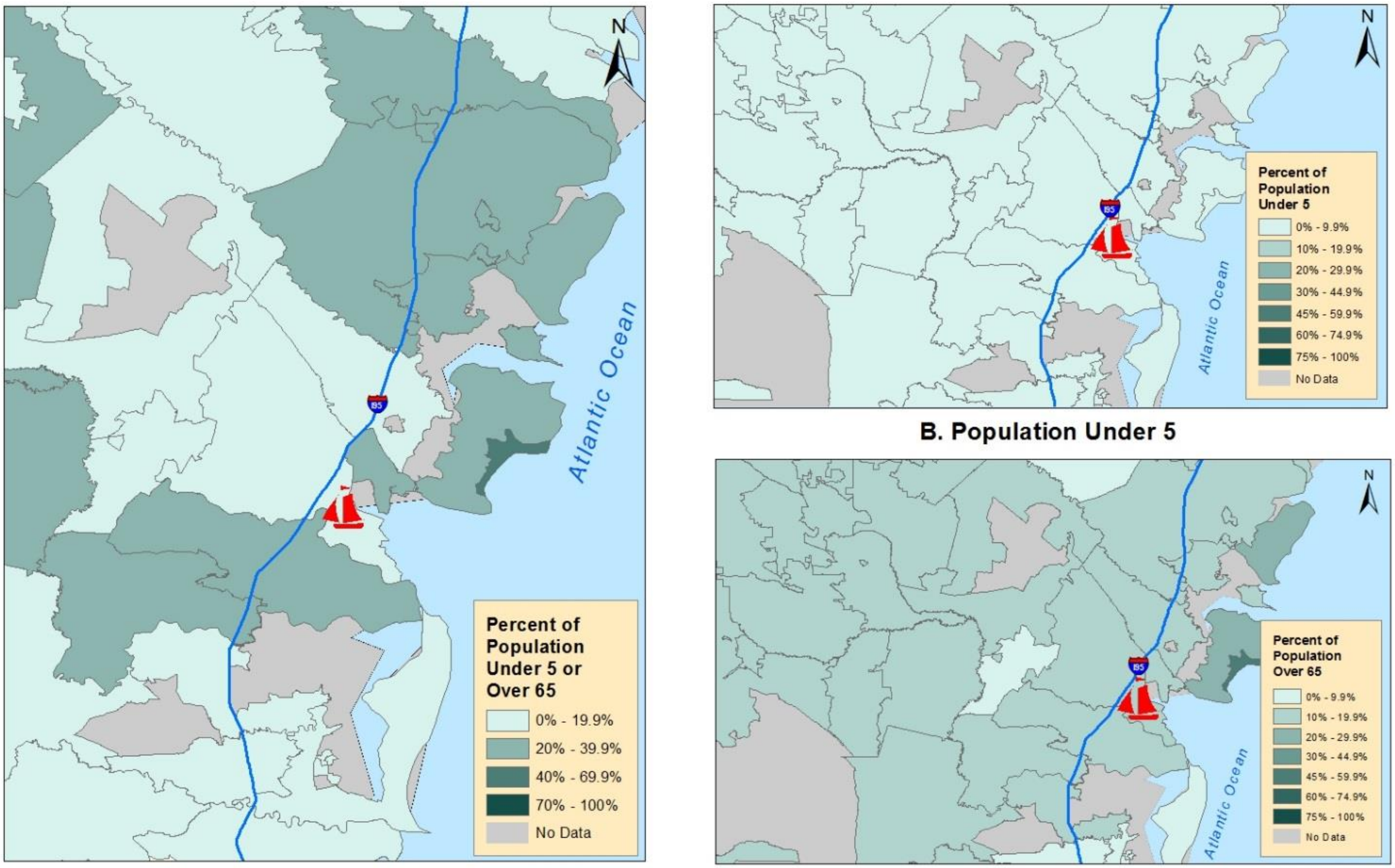


B. Population Under 5

A. Population Under 5 or Over 65

C. Population Over 65

Figure 19: Population demographics for age in census block grounds surrounding the Port of Houston

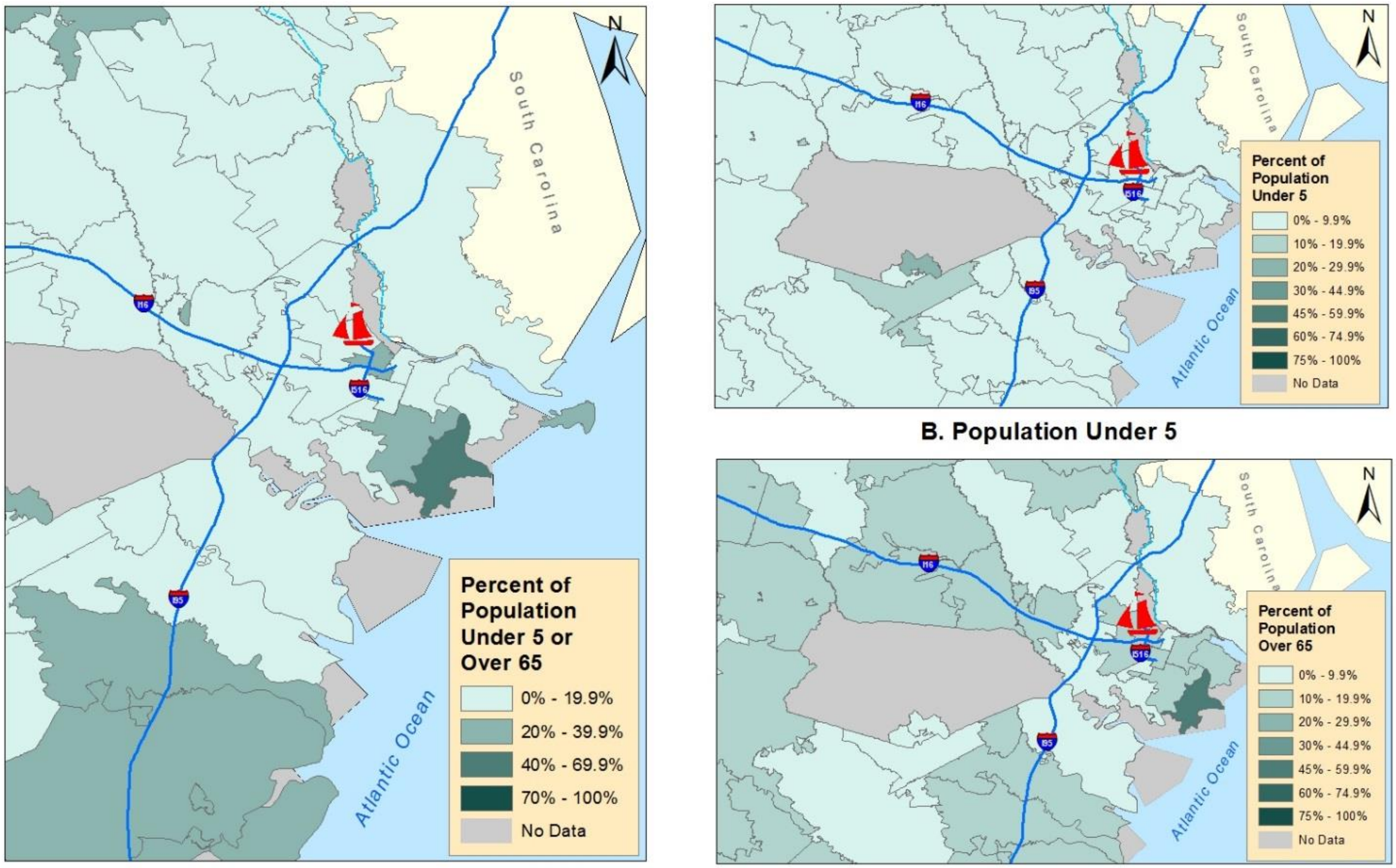


B. Population Under 5

A. Population Under 5 or Over 65

C. Population Over 65

Figure 20: Population demographics for age in census block grounds surrounding the Port of Brunswick



B. Population Under 5

A. Population Under 5 or Over 65

C. Population Over 65

Figure 21: Population demographics for age in census block grounds surrounding the Port of Savannah

3.6. Linguistic Isolation

This section looks at the linguistic isolation of the census tract areas surrounding each port. Households in which all members 14 years and older speak do not speak English and who have difficulty speaking English are considered linguistically isolated. The EPA's EJSCREEN tool provides the data used to create the figures in this section.

Figure 22 shows the percentages of the population living in linguistic isolation for census block groups in Los Angeles, California with the locations of the Port of Los Angeles and Port of Long Beach indicated in red.

Figure 23 shows the percentages of the population living in linguistic isolation for census block groups in Houston, Texas with the different locations of the Port of Houston indicated in red.

Figure 24 shows the percentages of the population living in linguistic isolation for census block groups in Brunswick, Georgia with the location of the Port of Brunswick indicated in red.

Figure 25 shows the percentages of the population living in linguistic isolation for census block groups in Savannah, Georgia with the location of the Port of Savannah indicated in red.

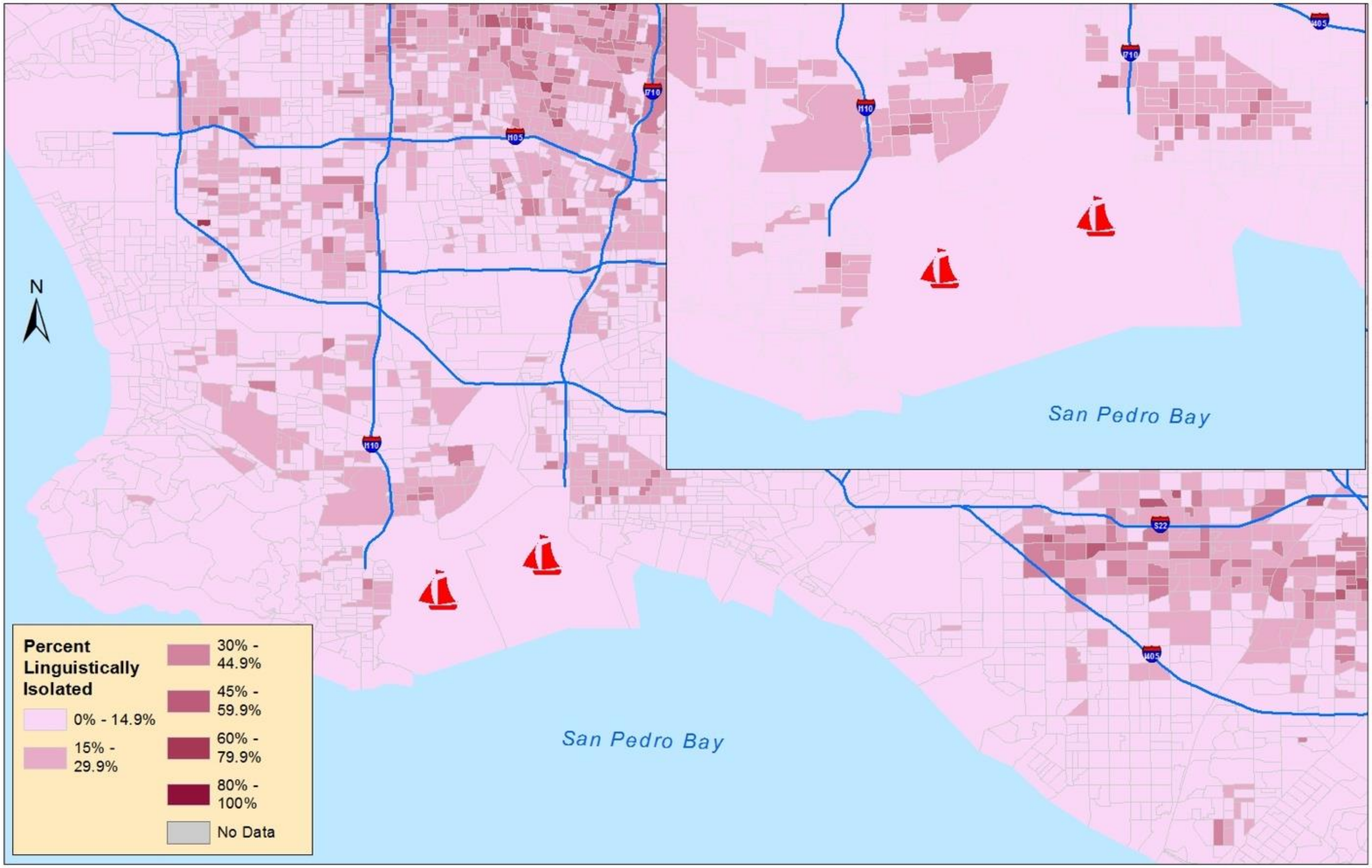


Figure 22: Percentages of linguistically isolated populations surrounding the Port of Los Angeles and Port of Long Beach

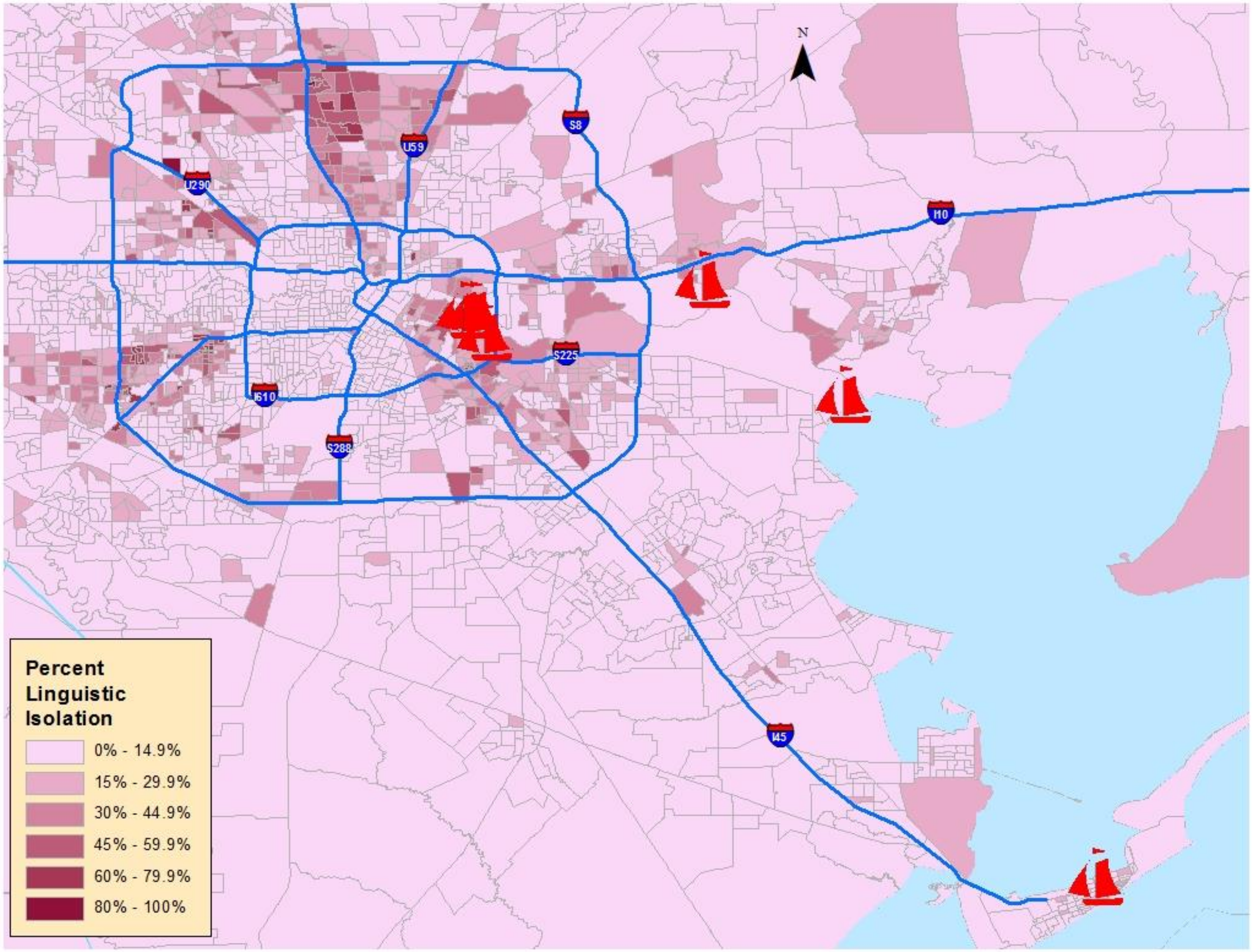


Figure 23: Percentages of linguistically isolated populations surrounding the Port of Houston

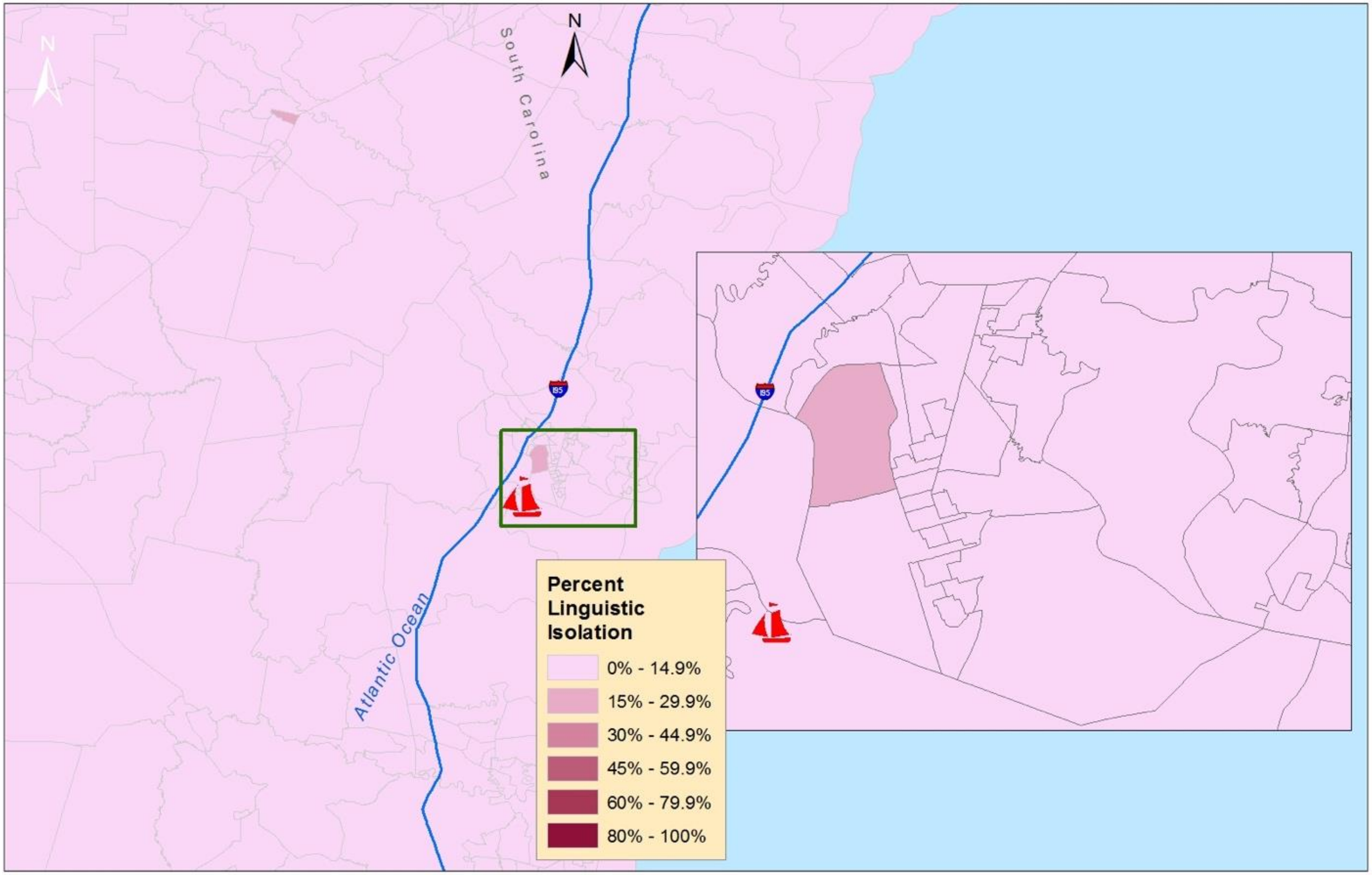


Figure 24: Percentages of linguistically isolated populations surrounding the Port of Brunswick

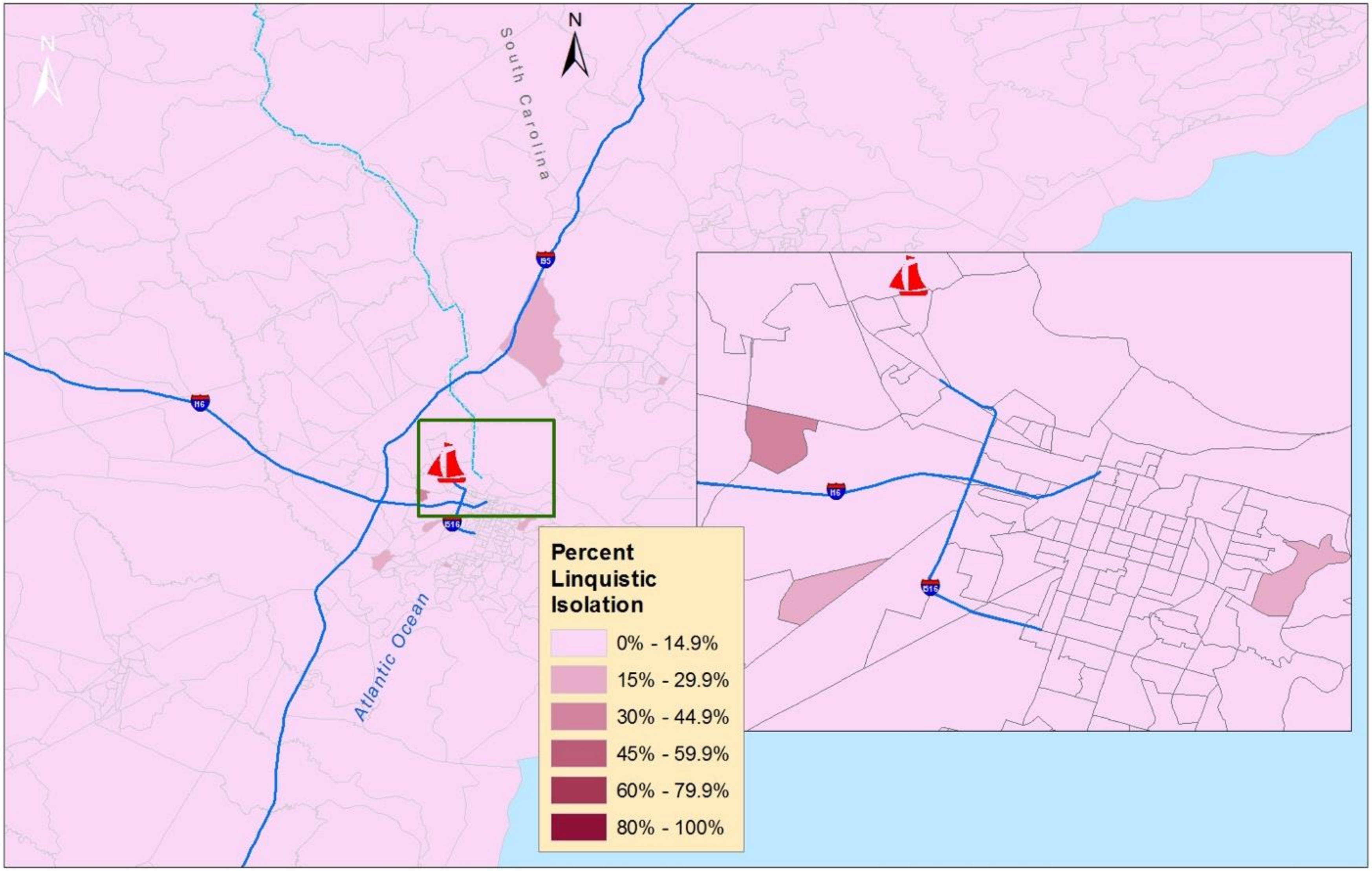


Figure 25: Percentages of linguistically isolated populations surrounding the Port of Brunswick

3.7. Education

This section looks at the education status of the populations living in the census tract areas surrounding each port. Education status is determined by the percentage of the population in each census tract age 25 and older without a high school diploma. The EPA's EJSCREEN tool provides the data used to create the figures in this section.

Figure 26 shows the percentages of the population over age 25 with less than a high school degree for census block groups in Los Angeles, California with the locations of the Port of Los Angeles and Port of Long Beach indicated in red.

Figure 27 shows the percentages of the population over age 25 with less than a high school degree for census block groups in Houston, Texas with the different locations of the Port of Houston indicated in red.

Figure 28 shows the percentages of the population over age 25 with less than a high school degree for census block groups in Brunswick, Georgia with the different locations of the Port of Brunswick indicated in red.

Figure 29 shows the percentages of the population over age 25 with less than a high school degree for census block groups in Savannah, Georgia with the different locations of the Port of Savannah indicated in red.

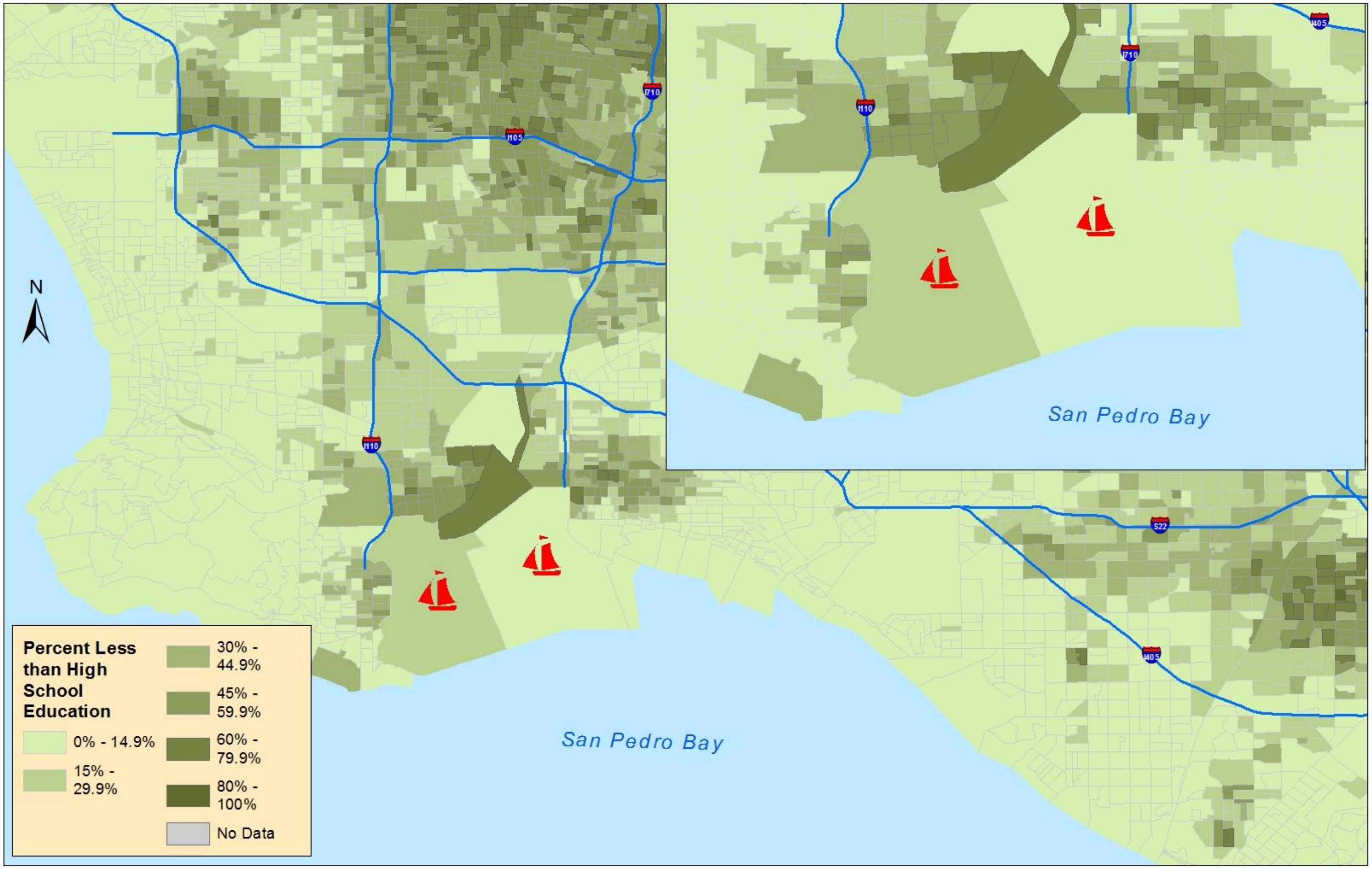


Figure 26: Percentages of the population over age 25 with less than a high school education surrounding the Port of Los Angeles and Port of Long Beach

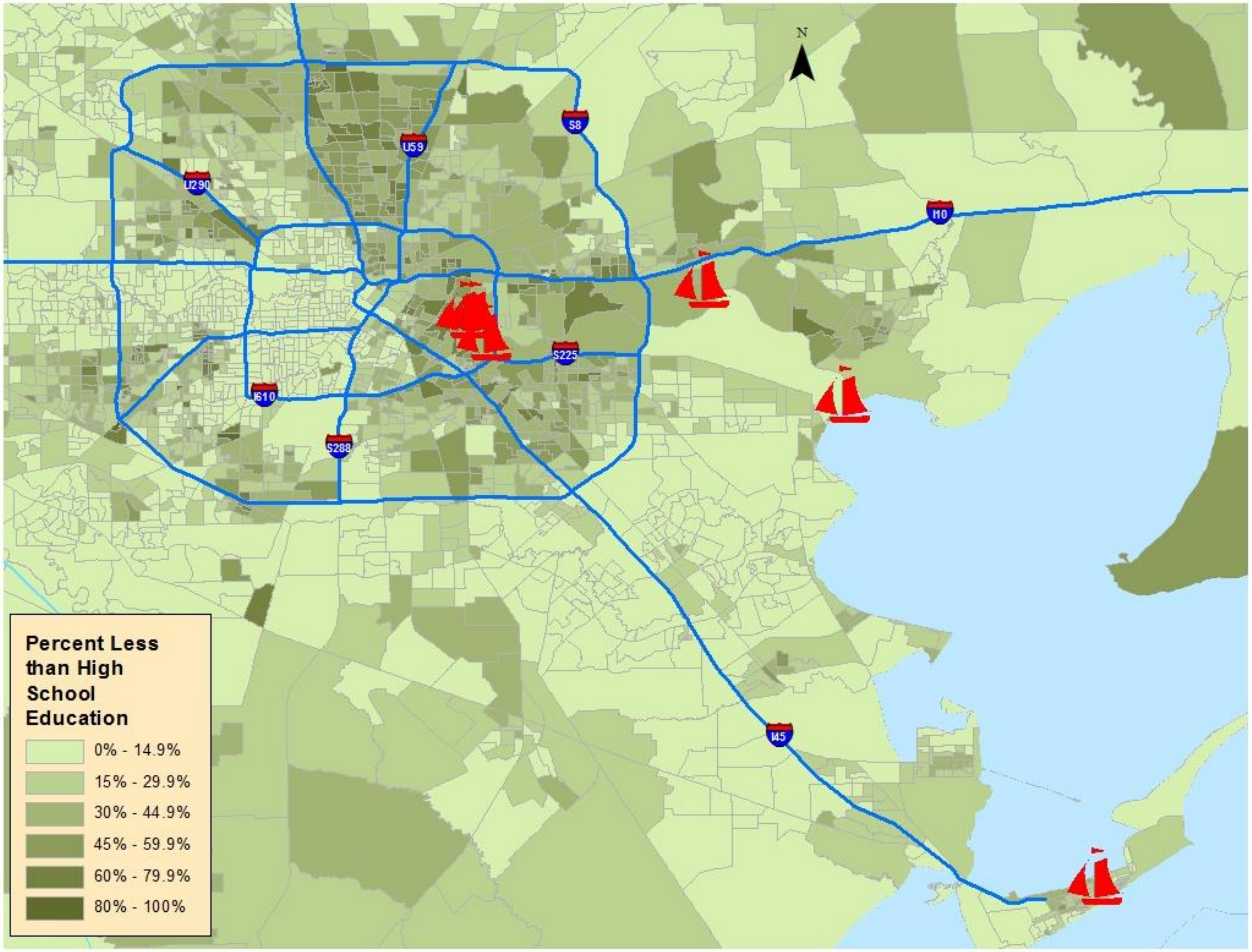


Figure 27: Percentages of the population over age 25 with less than a high school education surrounding the Port of Houston

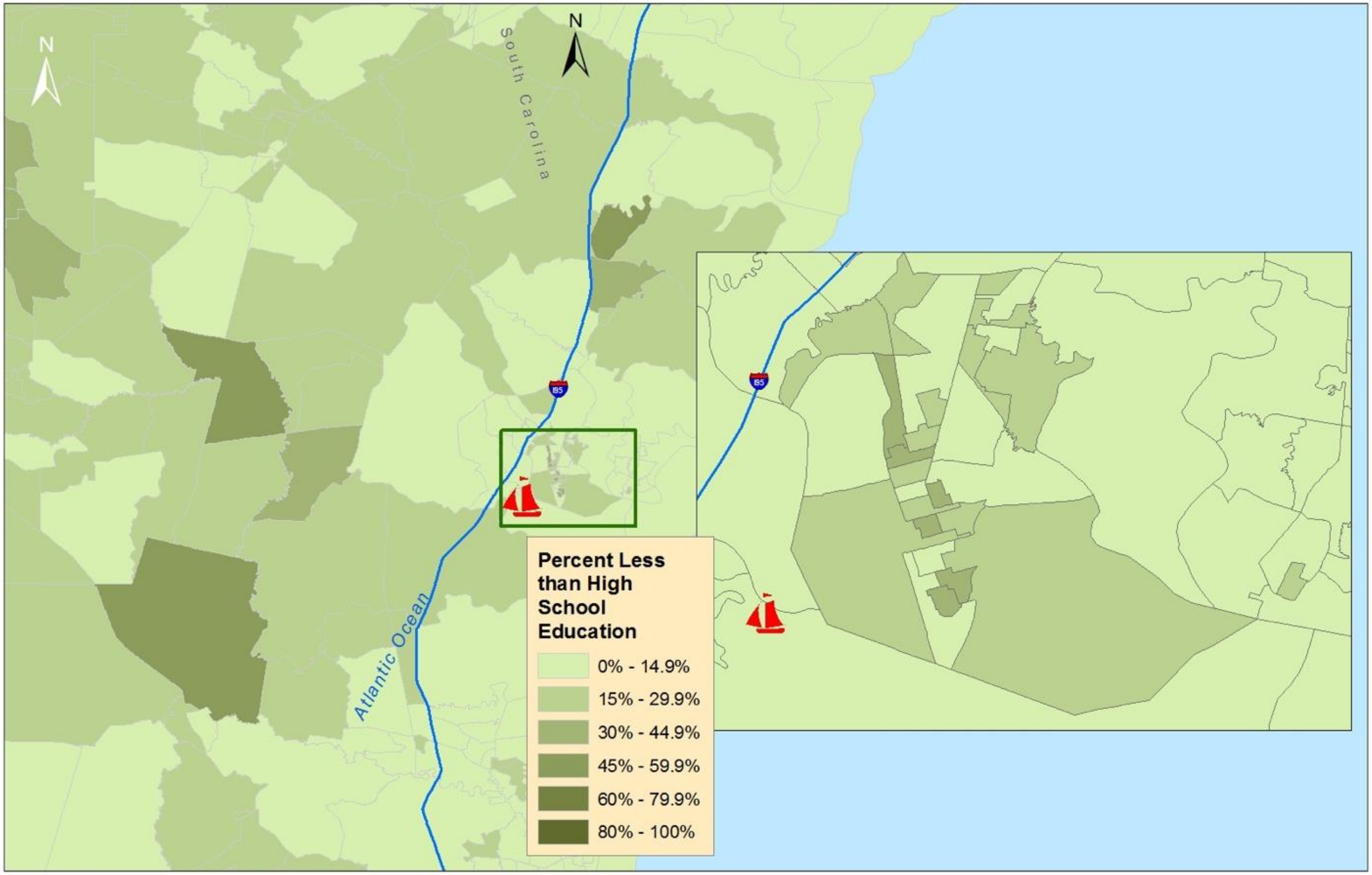


Figure 28: Percentages of the population over age 25 with less than a high school education surrounding the Port of Brunswick

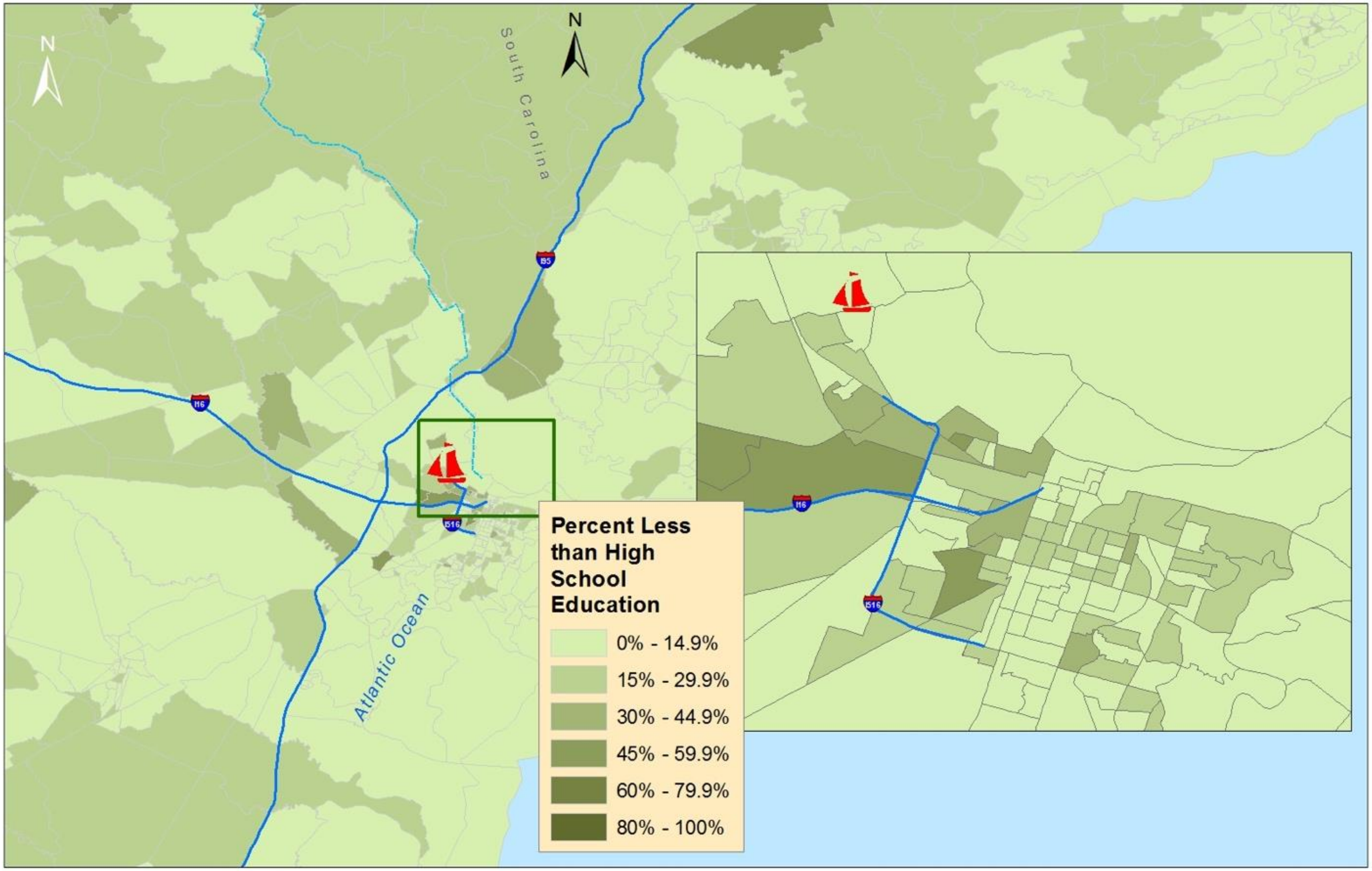


Figure 29: Percentages of the population over age 25 with less than a high school education surrounding the Port of Savannah

4. MODELING EMISSIONS FROM TRUCKS IDLING AT PORT GATES

This section presents a preliminary assessment of air quality model configuration based on EPA guidance documentations for air quality modeling and the results from the literature review. The findings from this section will allow the CARTEEH project team to create the best data collection and modelling plan that gives the best understanding of population exposures related to port emissions. The assessment detailed in this section is organized by the nine-step process given in the EPA's *Transportation Conformity Guidance for Quantitative Hot-Spot Analyses in PM2.5 and PM10 Nonattainment and maintenance Areas* with the process for each step applied to the CARTEEH project (United States Environmental Protection Agency, 2015). This thesis does not provide a comprehensive modeling plan for modeling emissions generated by trucks idling at port gates, but evaluates several components of the modeling plan to determine the best steps going forward for the CARTEEH Ports project.

1. *Determine Need for a PM Hot-Spot Analysis*

The first step in conducting a PM Hot-Spot Analysis is to determine if there is a need for a conformity analysis. The EPA guidance provides a list of the five types of projects that require analysis. Even though the ports included in this study are not currently subject to a new conformity analysis as far as the author is aware, this analysis still follows the guidance prescribed by the EPA to determine the best approach, model selection, and data requirements.

2. *Determine Approach, Models and Data*

Step two of the conformity analysis includes determining the area and emissions sources to be included in the analysis. The Port of Houston was selected as the study location for this project. The Port of Houston has several different areas where ships can load and unload cargo in addition to the Port of Galveston just south of the city of Houston. Only one location of the port was considered for this analysis, which is indicated by Figure 30. As previously mentioned, some of the ports are shown as being inland and not located directly on the coast. These ports are connected by a series of rivers and channels which are not shown on the map. The river network connecting the ports is most extensive for the Port of Houston, and some locations of the port are more than 30-kilometers inland.

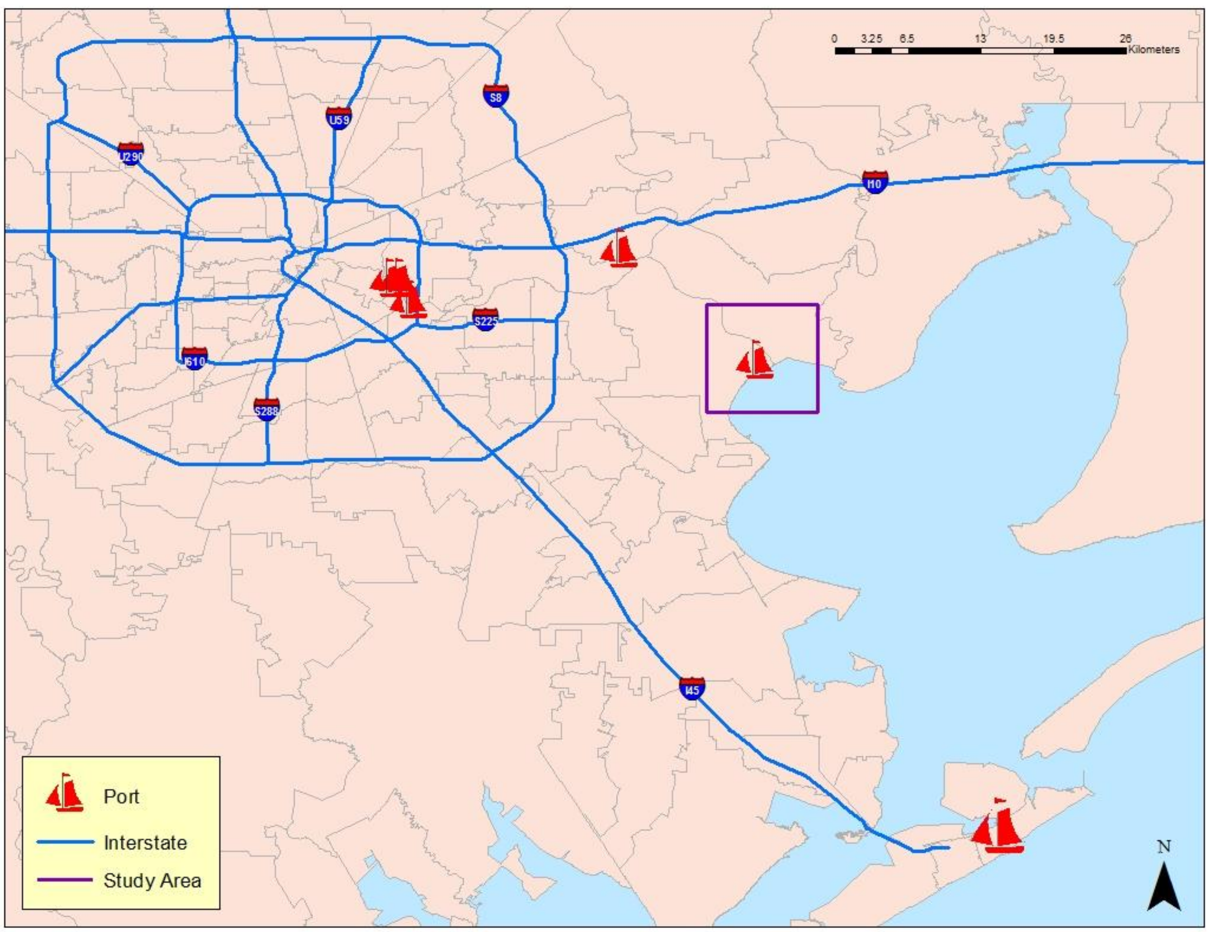


Figure 30: Locations for the Port of Houston with the study area outlined in purple

The waiting area for idling trucks outside of the port gate was estimated to be a 100-meter by 200-meter area based on aerial imagery of the idling areas at several of the ports included in the study. The size of the idling area is not significant to this analysis, as all scenarios will use the same idling area size so this parameter will be uniform across all test cases.

The second part of step two of the guideline is determining the emission sources which should be modeled. For this analysis, emissions from trucks idling at port gates will be the only emission source considered. Because fine and ultra-fine particulate matter is the primary constituent of diesel exhaust, PM2.5 will be the only pollutant modeled as part of this analysis (Wichmann, 2007). In modeling the emissions from idling trucks, emission rates for different vehicle model years are included to account for potential variations in idling emission rates. Using different model year's emission rates in the analysis is discussed in more detail in Section 4.1.

3. *Estimate On-Road Motor Vehicle Emissions*

Estimating on-road motor vehicle emissions is step three of the Hot-Spot conformity analysis process. The models recommended for this component of the analysis are EMFAC in California and MOVES in the rest of the United States. MOVES is the model used for this analysis as the study location is in Texas; however, in this case, MOVES was used to determine fleet age characterization instead of being used for on-road emissions modeling. On-road emissions were not included in this analysis because the primary objective of the analysis is to compare variations between different model configurations and not to comprehensively estimate population exposures. The larger research effort should include on-road motor vehicle emissions affecting populations surrounding the ports as these emissions significantly contribute to local air quality. One study confirmed that the air quality impacts of through-traffic emissions for communities living near the Ports of Los Angeles and Long-Beach are significant for local air quality and looked at contributions made by different vehicles types and road classes ((Wu, Houston, Lurmann, Ong, & Winer, 2009).

4. *Estimate Emissions from Road Dust, Construction, and Additional Sources*

In addition to considering on-road vehicle emissions, step 4 of the analysis methodology includes estimating emissions from road dust, construction, and heavy-duty equipment. These sources were excluded from this analysis as they are included later in the larger research effort. Locomotive emissions, re-entrained dust, and emissions generated by cranes and other freight handling equipment will be included in the final population exposure estimate but are not within the scope of this thesis.

5. *Select an Air Quality Model, Data Inputs, and Receptors*

Step five of the Analysis Guidance procedures includes selecting an air quality model, data inputs, and receptors. The guidance recommends using either AERMOD or CAL3QHCR for modeling the dispersion of emissions generated by a project, but specified which model should be used based on the type of project. For transit, freight, and other terminal projects, AERMOD is the recommended model as a large share of the emissions from these types of projects come from engine start and idling activities. Based on this recommendation, AERMOD is the model used in this analysis, as it is an examination of the emissions generated by idling vehicles at port gates.

Beyond the models recommended by the PM Hot Spot Analysis Guide (AERMOD and CAL3QHCR), CALPUFF and CMAQ are other models available for modeling PM2.5. In order to be thorough in the model selection portion of this analysis, these models were also considered. CALPUFF and CMAQ are used for large scale modeling and include the effects of chemical transformations. CALPUFF is used specifically for modeling puffs from activities such as power generation, or other elevated sources and includes long-range transport of an air parcel. Because this study is looking at tailpipe emissions, which are typically considered a surface source, long-range transport is not a huge issue and AERMOD is an acceptable model choice. Another consideration in model selection is AERMOD's limited treatment of chemical transformations. Because PM2.5 emitted from truck tailpipes is a primary source, it is not important to include chemistry as secondary sources are not being considered (Hodan & Barnard, 2013).

The next decision to make, once AERMOD has been selected to model emissions for this analysis, is how the emissions will be represented in the model. The modeler has a choice between an area, volume, point and line source. For this analysis, the idling trucks are classified as an area source as these vehicles are idling in flat, 2-dimensional areas and the emissions are generated from this area. The dimensions of the idling area are set as a 100-meter by 200-meter area based on aerial imagery of the idling areas at several of the ports included in the study. One example of an idling area for the study location at the Port of Houston is shown in Figure 31, which represents a typically idling area at port gates (Google, 2017). It was assumed that 100 vehicles were idling within this area and this assumption was held constant across all model runs. This assumption for the number of trucks idling is an underestimate for the capacity of the idling area based on size, but accounts for daily variations in the number of vehicles idling and for ease of calculation. Knowing the exact number of vehicles is not important for the scope of this project, as the purpose is to vary other inputs for the air quality model and analyze how these variations impact estimated concentrations.

Figure 31: Dimensions of the idling area used for model configuration at the selected study location for the Port of Houston

AERMOD requires meteorological data to characterize dispersion of pollutants due to mechanical and convective processes in the boundary layer, with mechanical process being more important for transportation projects as these emissions are released near the ground (United States Environmental Protection Agency, 2015). Meteorology used in this analysis was collected from the Texas Commission for Environmental Quality (TCEQ) which provides pre-processed AERMET surface profiles and upper air data (Texas Commission on Environmental Quality, 2017). AERMET is the program used for pre-processing meteorological data in the input format required by AERMOD. AERMET data was collected for the 2015 model year, from the Harris county weather station located at the George Bush Intercontinental Airport. The data collected for this study is considered representative of the project area as the airport is located 48 kilometers (30 miles) from the selected Port. The surface characteristics of the monitoring site are also assumed to be representative of the study area as there is not significant variation of elevation in coastal areas (airport elevation is 75 feet higher) and so flat terrain was assumed for all model runs. Additionally, both locations are in urban areas so the study location was specified as an urban source in AERMOD. The percentage of missing meteorological data for the 2015 data set is

0.23%, which is less than 10% as required by the EPA so no additional meteorological data processing is required.

The overall purpose of this research effort is estimating population exposures as a result of port operations. A key component of estimating population exposures is placing receptors in appropriate locations. Receptors should be placed in areas substantially effected by the project, and in areas where high concentrations are expected to occur (United States Environmental Protection Agency, 2015). The EPA considers AERMOD results to be applicable to a distance of 50 kilometers (31.1 miles) surrounding the source. A study, presented to the EPA in 2012, found that 20 kilometers (12.4 miles) may be a more appropriate distance to apply AERMOD results (Paine, 2012). Based on these findings about limitations to the area AERMOD may reasonably be applied to, three different scales of receptor placement were used with receptors densely located closer to the source (Wu & Niemeier, 2016). In areas close to the source, receptors are spaced at 100-meter intervals in a 500-meter radius from the port with some receptors located inside of the areal source. Further from the study location receptors are placed at 1-kilometer intervals in a 10-kilometer radius from the port, and at 3-kilometer intervals in a 30-kilometer radius from the port as shown in Figure 32 for the study location at the Port of Houston. The receptor locations indicated by the figure are held constant between all model runs.

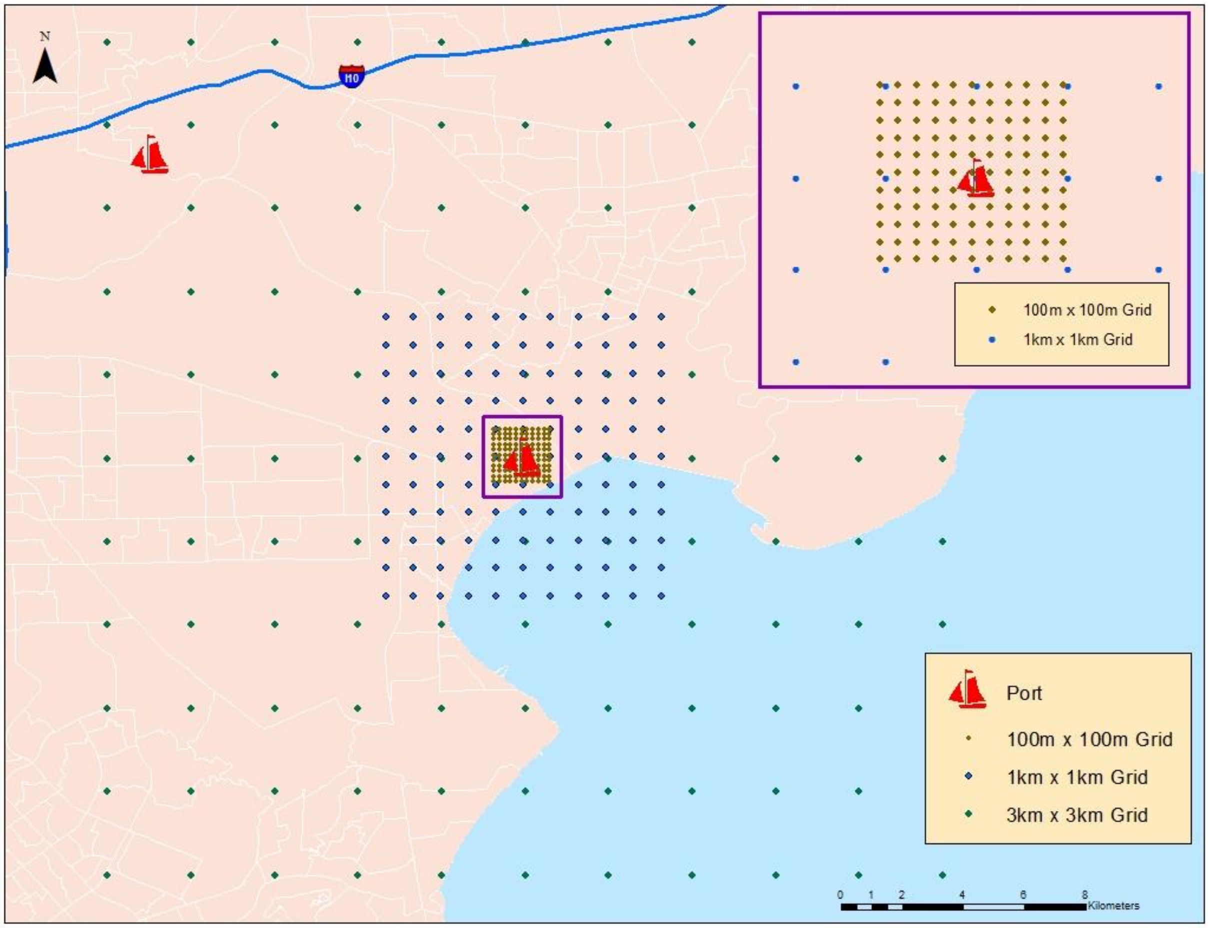


Figure 32: Receptor grid system for the Port of Houston

6. Determine Background Concentrations from Nearby and Other Sources

This step of the PM Hot Spot Analysis Process for transportation projects includes collecting data for background concentrations from nearby and other sources. These sources are not included in this analysis as this is not a comprehensive population exposure assessment. Background concentrations are included in the final step of the population exposure assessment which also incorporates emissions generated by rail, shipping and freight handling operations occurring at the port.

7. Calculate Design Values and Determine Conformity

The PM Hot Spot Analysis Guide recommends calculating design values to determine conformity; however, this step is not included in this analysis as there is not a build/no-build scenario being considered and thus there is no need to check for conformity of the project.

8. *Consider Mitigation or Control Measures*

The PM Hot Spot Analysis Guide recommends considering mitigation or control measures; however, this step is not included in this analysis as there is no build/no-build scenario being considered and thus there is no need to consider mitigation or control measures to reduce project emissions to ensure conformity requirements are met. Section 2.3 of this thesis discusses several emission reduction strategies currently in use to reduce idling emissions outside of ports. These strategies could also be considered for application to the ports considered as part of the CARTEEH Ports Project.

9. *Document the PM Hot-Spot Analysis*

This thesis serves as documentation for the portions of the PM Hot-Spot Analysis relevant to this project. This documentation includes a brief project description, analysis years, emissions modeling procedures, and modeling inputs used to generate air quality modeling data as well as model results comparison.

Sections 4.1-4.3 of this thesis look at three different variations in input data for modeling emissions from trucks idling at port gates. Section 4.1 examines the effects variability in vehicle age has on estimated concentrations with four different average vehicle age scenarios considered. Section 4.2 examines the effect different years' meteorological data has on estimated concentrations. Section 4.3 examines the effect variations in the roughness parameter have on model results. The spatial scale, location, and receptor locations are held constant for model configuration in all three sections.

4.1: Variations in Vehicle Age

In an effort to most accurately estimate population exposures, it is important to consider if characterizing the model year of idling trucks should be included as part of the data collection process. Collecting license plate information in order to obtain vehicle model years will lead to the most accurate estimation of the areal emission rate; however, this step may not be necessary and will certainly add to the cost and complexity of the data collection and processing steps. Determining if characterizing the vehicle age of an idling fleet is necessary for an accurate population exposure estimate is the focus of this section.

Different model years have different emission rates as indicated in Table 4, with older model years generally having higher PM2.5 emission rates than newer models (United States Environmental Protection Agency, September 1, 2015). One variation in this trend can be seen for model years 1960-1993 which have lower PM2.5 emission rates than some of the younger models. This unexpected variation is most likely attributable to engine replacement for older vehicles. Diesel engines have to be replaced or rebuilt after extended use and so older truck models are often fitted with newer engines. The drastic emissions improvements from the 2006 to 2007 model year groups can be explained by the addition of SCR systems using DEF to reduce emissions. These systems were installed on many 2007 tucks to meet 2010 EPA emissions standards (Diesel Technoogy Forum, n.d.). The variation in emission rates shown in Table 4, multiplied across many vehicles idling in a constrained area leads to a wide range of potential areal emission rates. These emissions rates, then lead to varying levels of population exposures in the areas surrounding ports.

Table 4: PM2.5 emission rates for heavy duty truck with vehicle model years ranging from 1960-2016

Model Year	PM2.5 Emission Rate (g/truck/hour)
2016+	0.24
2007-2016	0.35
2003-2006	5.56
1998-2002	6.16
1994-1997	6.44
1960-1993	4.21

The distribution of vehicle fractions by age is included in MOVES for heavy duty trucks given a project's analysis year. National default age distributions are provided in MOVES; however, the use of state or local age distributions is recommended unless this data is unavailable. Age distributions used for this analysis are based on the national default as this analysis is focused on variations between age distributions and not accurately estimating emissions generated by a specific location's age distribution. Table 5 provides the national default age distribution given as a fraction for each model year of combination long-haul trucks (US Environmental Protection Agency, January 2016).

Model year distributions were varied from the national default to consider a younger fleet and older fleet and then compare how the different fleet ages affect estimated concentrations. The different model year distributions used for this analysis will be referred to by its average vehicle age. The average vehicle age for the national default distribution is 7.5 years. Other sources have estimated that the average vehicle age for heavy duty trucks was 11.5 years old in 2016, and so this average vehicle age is also included in the analysis (Woodall, 2016). In order to account for younger fleets, an average vehicle age of 5 years is also included in the analysis. On the other end of the spectrum for average vehicle age, an average vehicle age of 14 years is included to account for the possibility of older fleets. The distribution of vehicle fractions by age for each of the four fleet averaged ages is included in Table 6.

Table 5: 2011 Age Fractions for MOVES Source Type 62, Combination Long-Haul Truck

Vehicle Age	Age Fractions	Vehicle Age (continued)	Age Fractions (continued)
0	0.0478	16	0.0209
1	0.0378	17	0.0127
2	0.0501	18	0.0086
3	0.0392	19	0.0052
4	0.1371	20	0.004
5	0.1028	21	0.0031
6	0.0971	22	0.0031
7	0.0584	23	0.0019
8	0.057	24	0.0032
9	0.0415	25	0.0009
10	0.0482	26	0.0009
11	0.0766	27	0.0007
12	0.0572	28	0.0003
13	0.0381	29	0.0004
14	0.0215	30	0.0004
15	0.0234		

Table 6: Distribution of vehicle fraction by age for each average fleet age

Model Year	14-year Average Vehicle Age	11.5 Year Average Vehicle Age	7.5-year Average Vehicle Age	5 Year Average Vehicle Age
2016+	0.0066	0.0856	0.0856	0.22
2007-2016	0.06	0.2644	0.6314	0.7
2003-2006	0.6314	0.4	0.1934	0.05
1998-2002	0.1934	0.1709	0.0708	0.03
1994-1997	0.0964	0.0224	0.0121	0
1960-1993	0.0122	0.0567	0.0068	0

From the vehicle-age fractions for each distribution, an overall areal emission rate was calculated. This calculation is based on the vehicle fractions provided in Table 6, and is calculated using Equation 1.

Equation 1

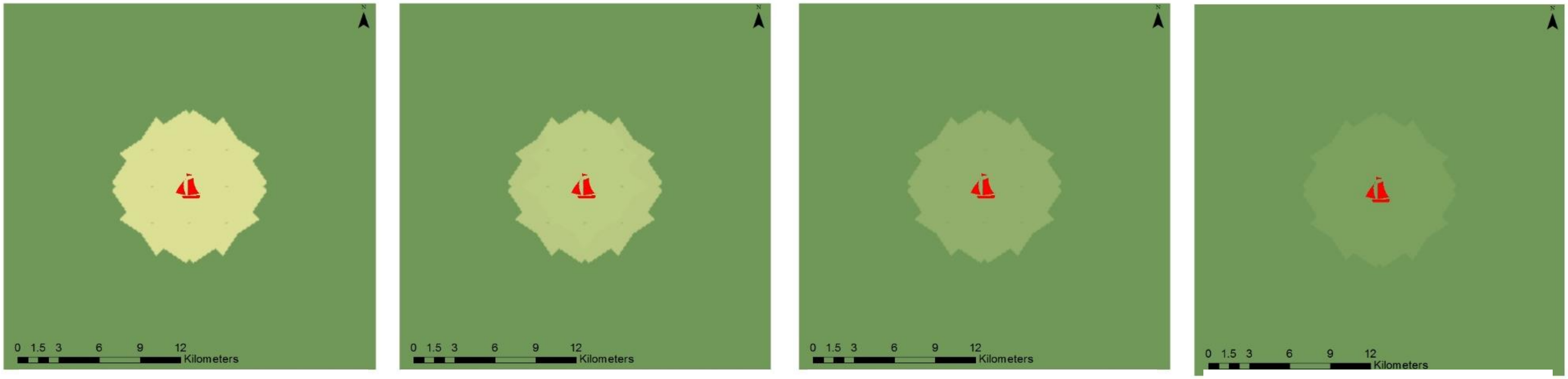
$$\sum_{1960\ Model\ Year}^{2016+Model\ year} \frac{Emission\ Rate\ (g/truck/hour) \times Vehicle\ Fraction \times 100\ vehicles}{Area\ of\ Source\ (20{,}000\ m^2)} \times \frac{1\ hour}{60\ second}$$

Using Equation 1, the overall areal emission rate was calculated for the four-average vehicle age model scenarios. The results from these calculations are shown in Table 7, and follow the expected trend that as average vehicle age decreases, so does the areal emission rate.

Table 7: Areal Emission Rate for Each Average Vehicle Age Modeling Scenario

Average Vehicle Age for Model Configuration	Areal Emission Rate $[g/s/m^2]$
14	4.50E-04
11.5	3.14E-04
7.5	1.55E-04
5	6.33E-05

Using the receptor locations specified in Figure 32, the areal emission rates given in Table 7, meteorology data from George Bush Intercontinental airport for 2015, and with the roughness parameter specified as low roughness, concentrations are modeled in AERMOD. Using the four different areal emission rates for different average vehicle ages, the concentration field calculated by AERMOD for the 3-kilometer grid scale is shown in Figure 33, the concentration field for the 1-kilometer grid scale is shown in Figure 34, and the concentration field for the 100-meter grid scale is shown in Figure 35.



Average Vehicle Age: 14 3-kilometer grid	Average Vehicle Age: 11.5 3-kilometer grid	Average Vehicle Age: 7.5 3-kilometer grid	Average Vehicle Age: 5 3-kilometer grid

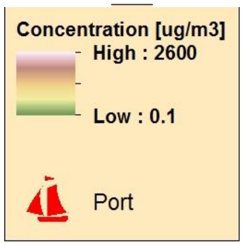
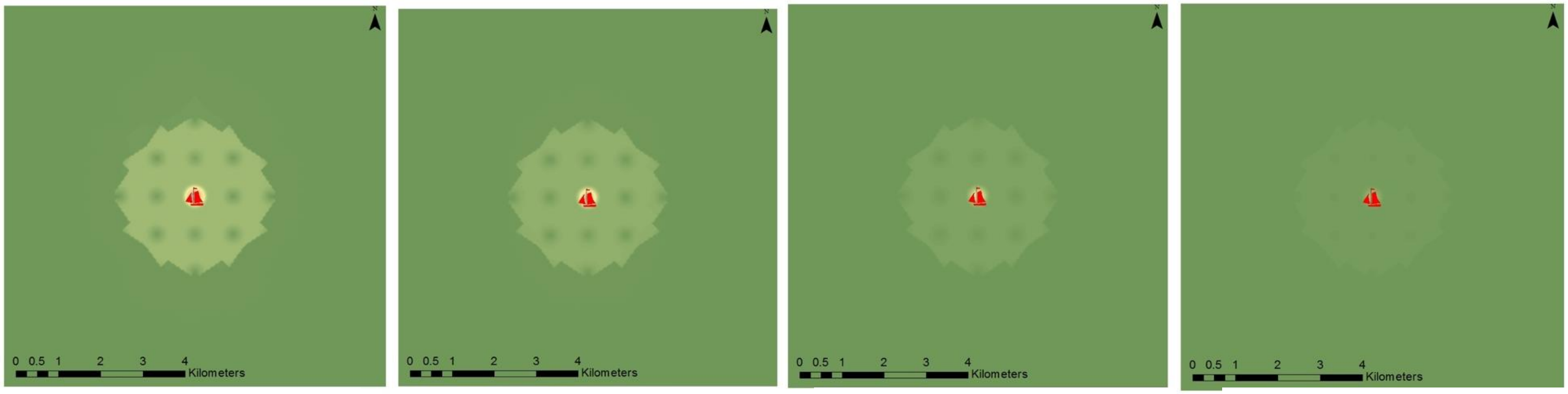


Figure 33: AERMOD results for a 15-kilometer radius surrounding the Port of Houston using 3-kilometer grid cells with average vehicle age in decreasing order and labeled beneath the figures



Average Vehicle Age: 14
1-kilometer grid

Average Vehicle Age: 11.5
1-kilometer grid

Average Vehicle Age: 7.5
1-kilometer grid

Average Vehicle Age: 5
1-kilometer grid

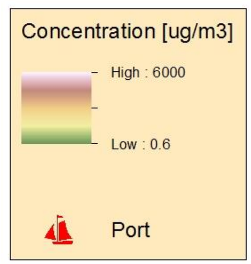
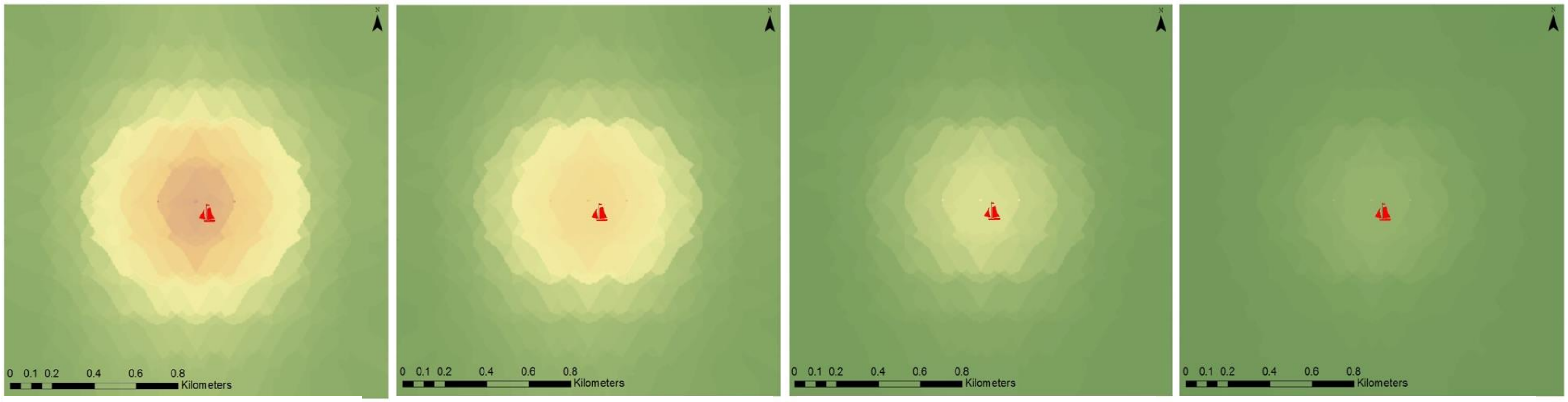


Figure 34: AERMOD results for a 5-kilometer radius surrounding the Port of Houston using 1-kilometer grid cells with average vehicle age in decreasing order and labeled beneath the figures



Average Vehicle Age: 14
100-meter grid

Average Vehicle Age: 11.5
100-meter grid

Average Vehicle Age: 7.5
100-meter grid

Average Vehicle Age: 5
100-meter grid

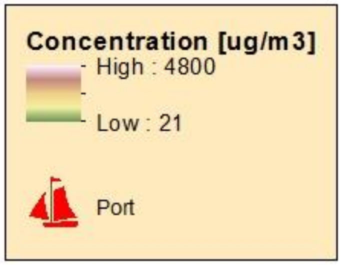


Figure 35: AERMOD results for a 500-meter radius surrounding the Port of Houston using 100-meter grid cells with average vehicle age in decreasing order and labeled beneath the figures

The model results were compared using frequency distribution plots as shown in Figure 36, Figure 37, and Figure 38

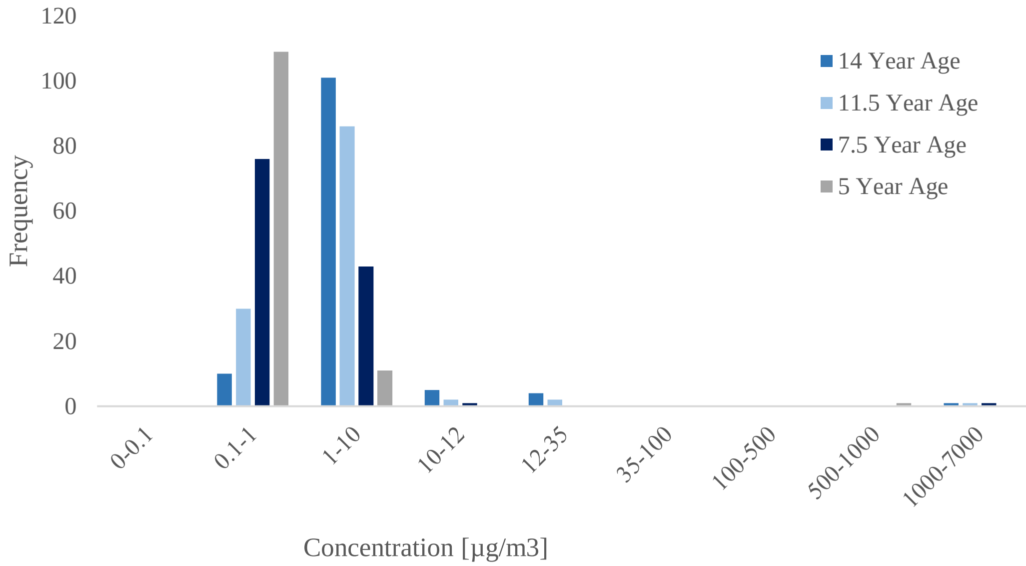


Figure 36: Frequency distribution for all average vehicle ages using 3-kilometer receptor spacing

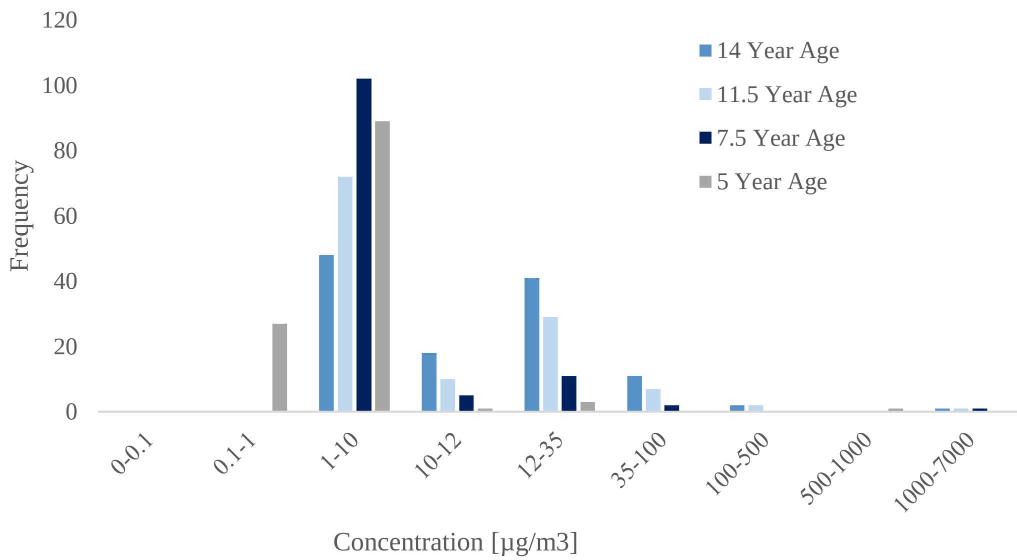


Figure 37: Frequency distribution for all average vehicle ages using 1-kilometer receptor spacing

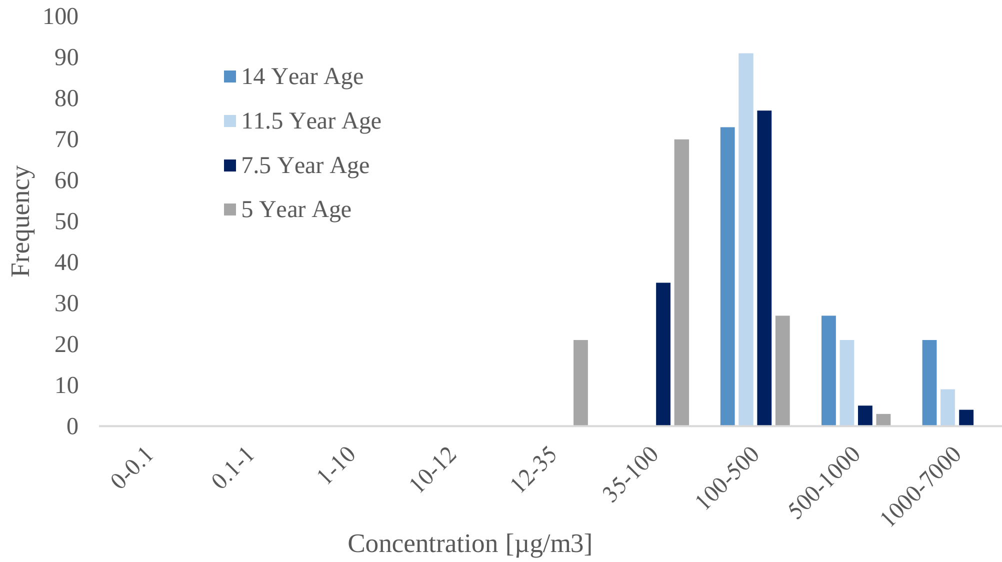


Figure 38: Frequency distribution for all average vehicle ages using 100-meter receptor spacing

Figure 36, Figure 37, and Figure 38show the model results for each spatial scale are clumped together along the x-axis. This clustered distribution within a smaller concentration range indicates that the concentrations estimated in AERMOD are within a set range, which is independent of the average vehicle age assumed for each model configuration. These figures also show the extent to which the truck emissions disperse as the distance from the idling area increases. Figure 38 shows that in a 500-meter radius around the idling area, concentration ranges predicted by AERMOD vary from $12 - 7000\ \mu g/m^3$ with 55.4% of the model results falling in the range of $100 - 500\ \mu g/m^3$. This range is the highest concentration range predicted for any of the spatial scales and also shows the highest variation in the model performance for the different average vehicle ages.

Figure 37 shows the concentration range for the 5-kilometer radius around the port varies from $0.1 - 500\ \mu g/m^3$ with 64.3% of the model predictions falling in the range of $1 - 10\ \mu g/m^3$. This total concentration range excludes the concentration estimations for the receptor locations within the idling area. The range where the majority of the model predictions fall for the 5-kilometer radius spatial scale is much closer to the acceptable range for annual PM2.5 given by the NAAQS; however, this range is expected to increase as background concentrations and emissions from other port operations are added.

Figure 36 shows the concentration range for the 15-kilometer radius around the port varies from $0.1 - 35\ \mu g/m^3$ with 46.5% of the model predictions falling in the range of $0.1 - 1\ \mu g/m^3$ and 49.8% of the model predictions falling in the range of $1 - 10\ \mu g/m^3$.

The clustered distribution of the concentrations predicted on each spatial scale for each average vehicle age gives a good indication that characterizing vehicle age is less important for accurately estimating population exposures. Characterizing vehicle age showed the lower impacts on concentrations estimated for populations living further than 500 meters from the port. This spatial distinction is important to consider particularly when considering population density in areas surrounding the ports. Figure 39 shows the population density for the communities surrounding the Port of Houston.

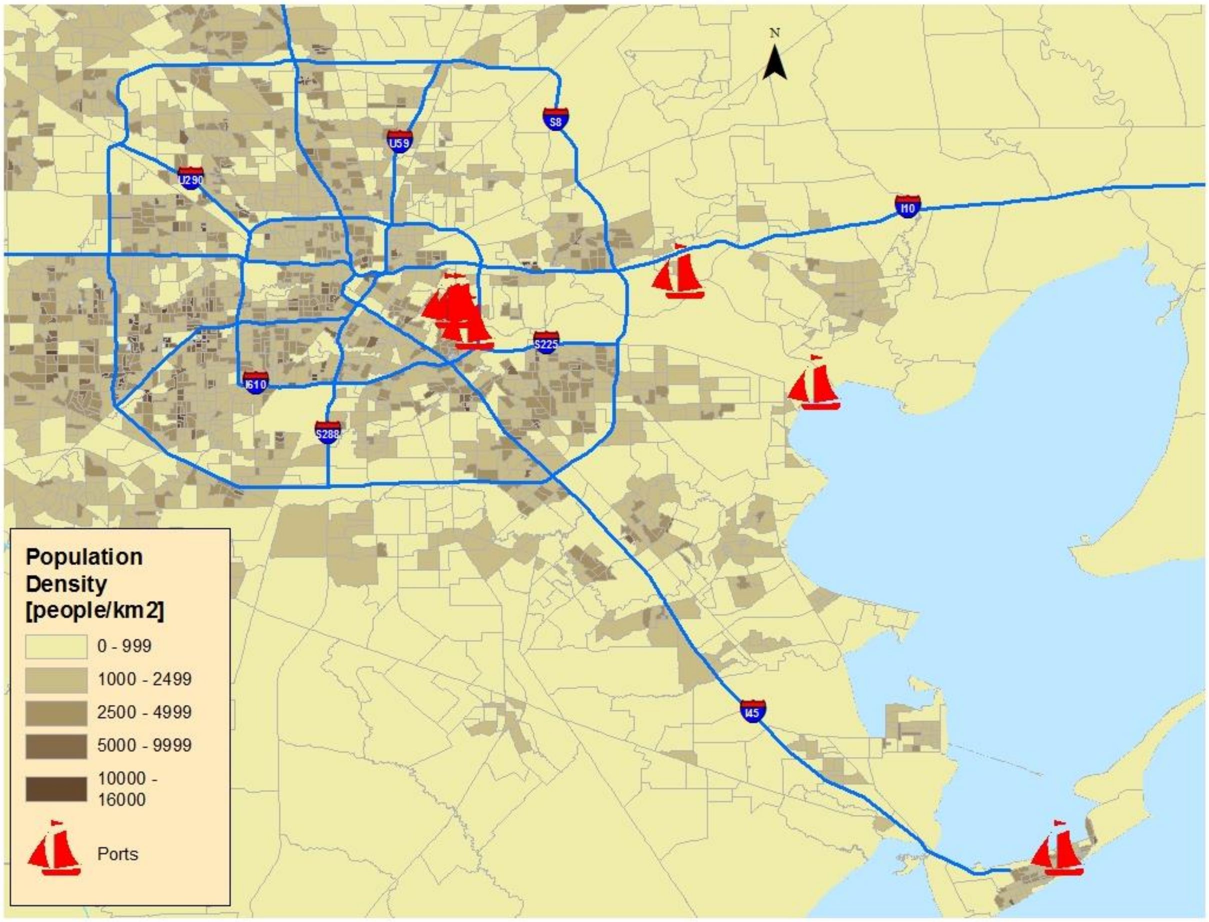


Figure 39: Population density by census block in the neighborhoods surrounding the Port of Houston

Table 8 shows how population density varies over the three spatial scales used air quality dispersion modeling. This information comes from US Census Bureau data. Population density is lowest in the 500-meter radius area surrounding the port, which is where estimated concentrations are the highest. The model results show that concentrations of PM2.5 are significantly dispersed further from the ports, as population density increases. This indicates that characterizing the vehicle ages for trucks idling outside of ports is not significant when estimating population exposures for populations living more than 500-meters from the port, which is where higher population density occurs.

Table 8: Population density in the areas surrounding the Port of Houston study location

Spatial scale surrounding the port (km)	Average population density [people/km^2]
0.5	105
5	870
15	1375

4.2: Variations in Year of Meteorological Data

This section follows the same format as the previous section using the receptor locations specified in Figure 32, the areal emission rates given in Table 7, the areal emission rate for a 7.5-year average vehicle age, with the roughness parameter specified as low roughness, and meteorological data from George Bush Intercontinental airport. Meteorological data for this section comes from the years 2011, 2012, 2013, 2014, and 2015 to compare model results with different meteorological data. The concentration field estimated by AERMOD is plotted in ArcGIS for each year's meteorological data.

Determining the effect different years meteorology has on the predicted concentrations is important for this research as AERMET files are typically not available from government agencies until the following calendar year or several months later. After data collection occurs for this project, the meteorological files needed to run AERMOD may not be available until late in the project timeline so being able to use previous years' meteorological data may be advantageous to the research team in analyzing the data they collect . The alternative to this would be collecting the AWOS station data and processing the AERMET and AERSURF files manually which can be technically challenging and requires extra time.

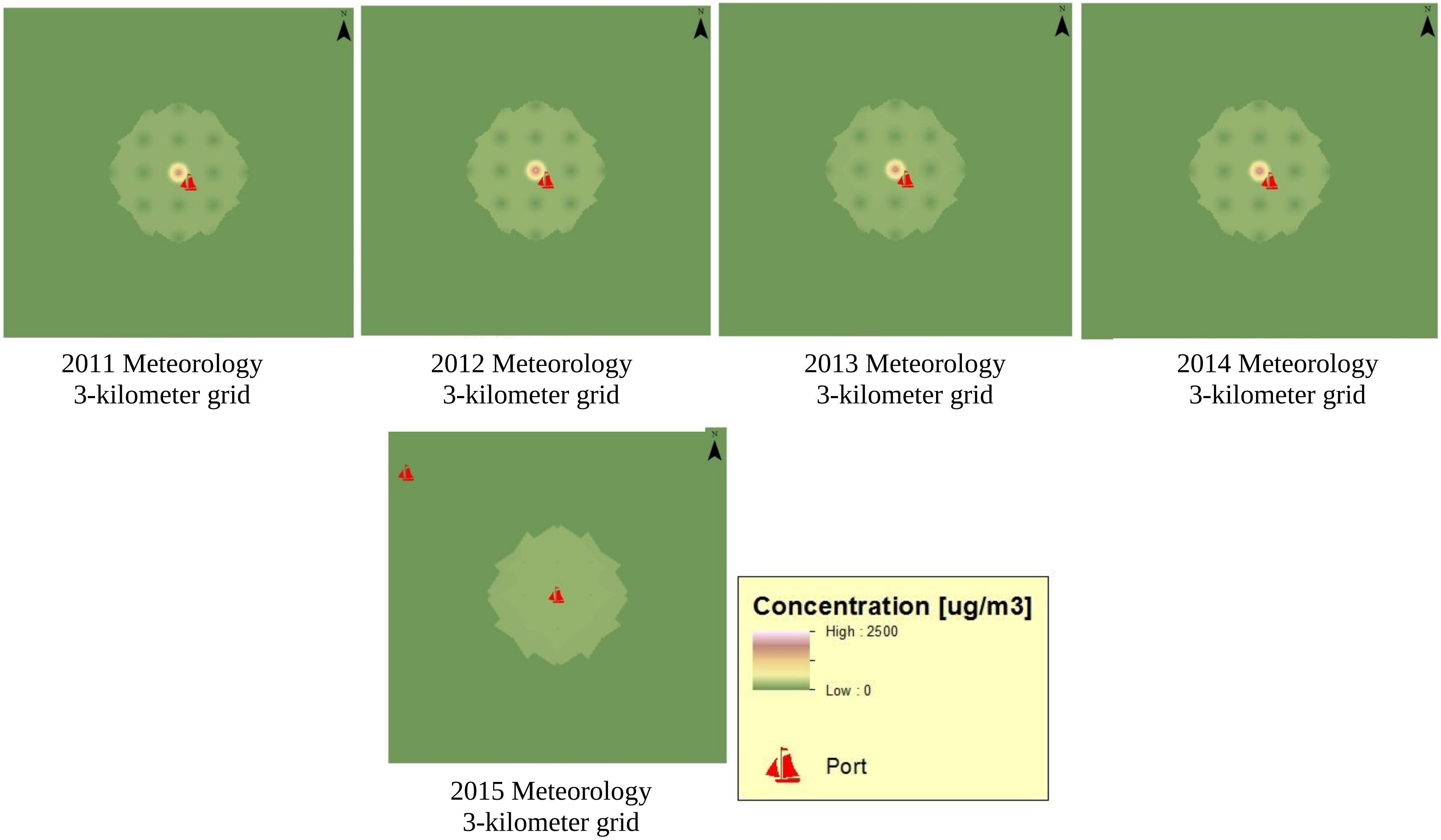
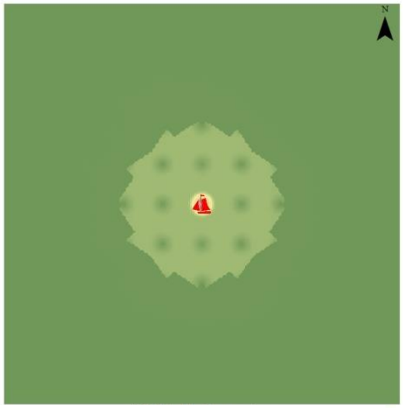
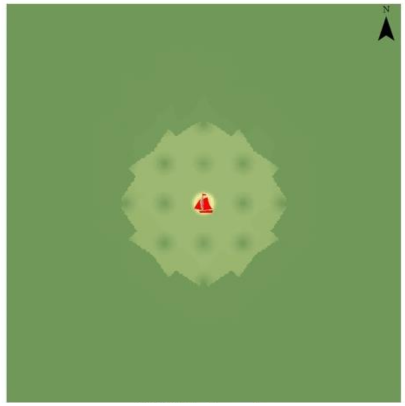
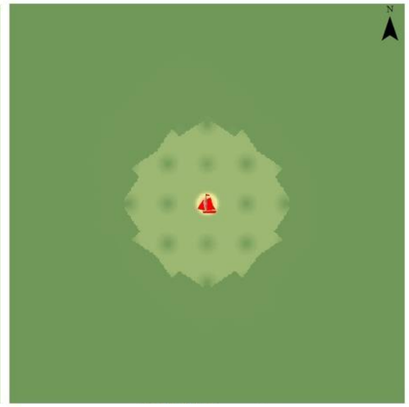
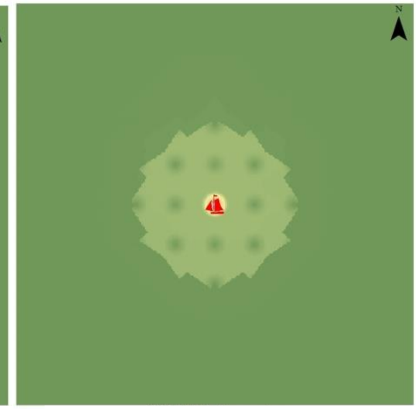


Figure 40: AERMOD results for a 15-kilometer radius surrounding the Port of Houston using 3-kilometer grid cells with 7.5-year average vehicle age in increasing year for meteorological data







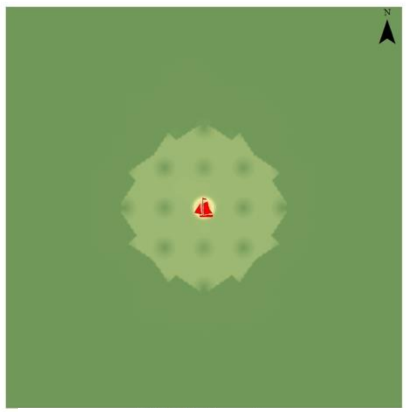


2011 Meteorology
1-kilometer grid

2012 Meteorology
1-kilometer grid

2013 Meteorology
1-kilometer grid

2014 Meteorology
1-kilometer grid



2015 Meteorology
1-kilometer grid

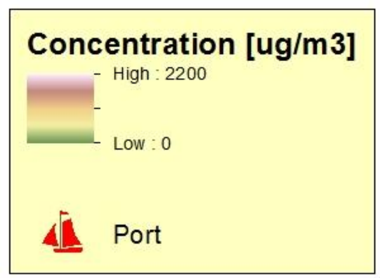


Figure 41: AERMOD results for a 5-kilometer radius surrounding the Port of Houston using 1-kilometer grid cells with 7.5-year average vehicle age in increasing year for meteorological data

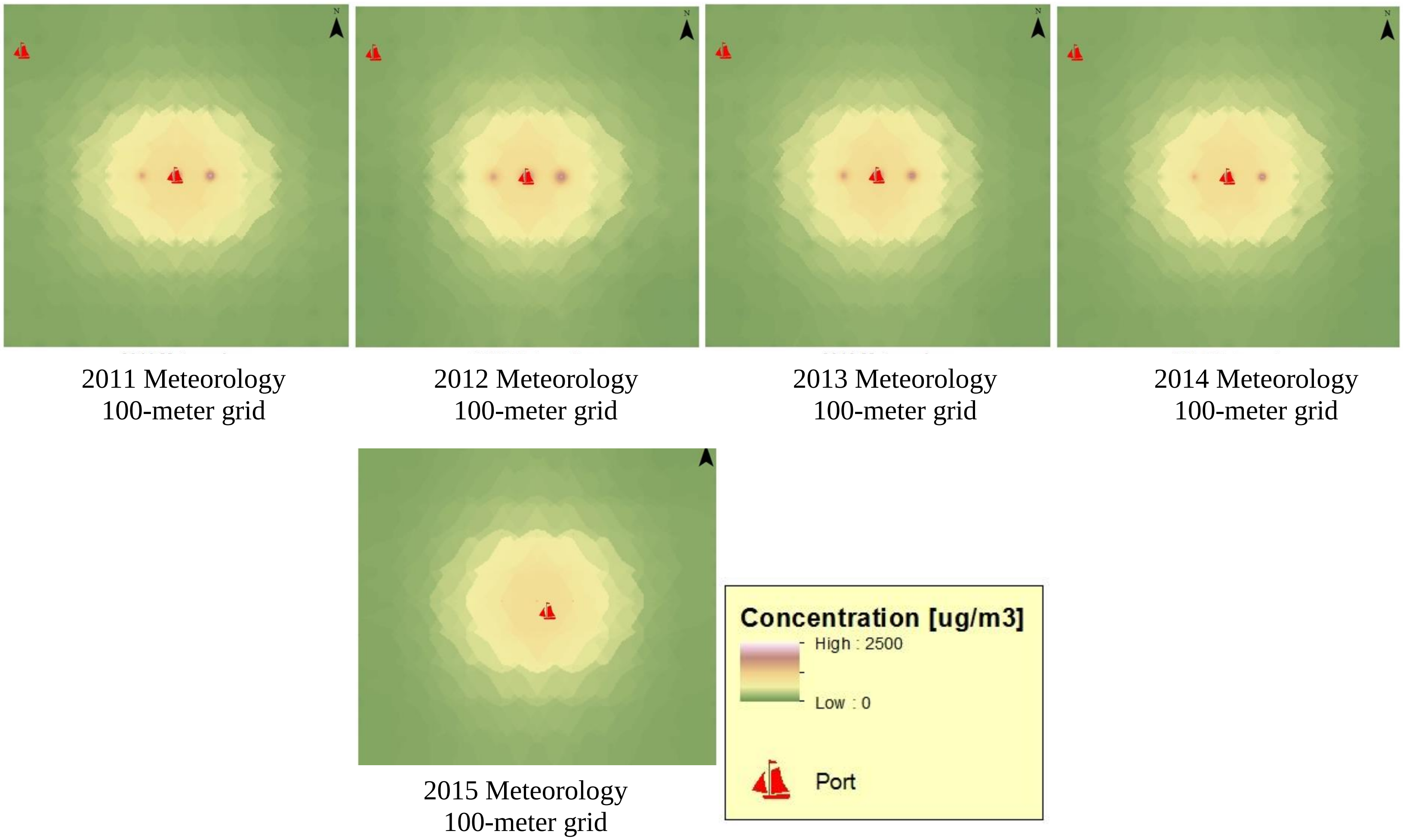


Figure 42: AERMOD results for a 1-kilometer radius surrounding the Port of Houston using 100-meter grid cells with 7.5-year average vehicle age in increasing year for meteorological data

The model results using different years' meteorology are compared using frequency distribution plots as shown in Figure 43, Figure 44, and Figure 45.

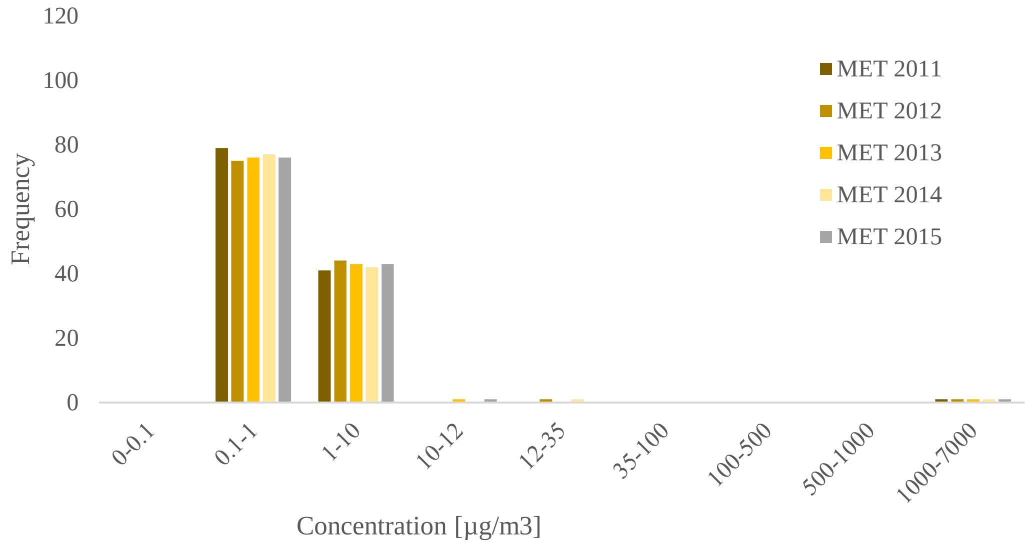


Figure 43: Frequency distribution for all years' meteorological data using 3-kilometer receptor spacing

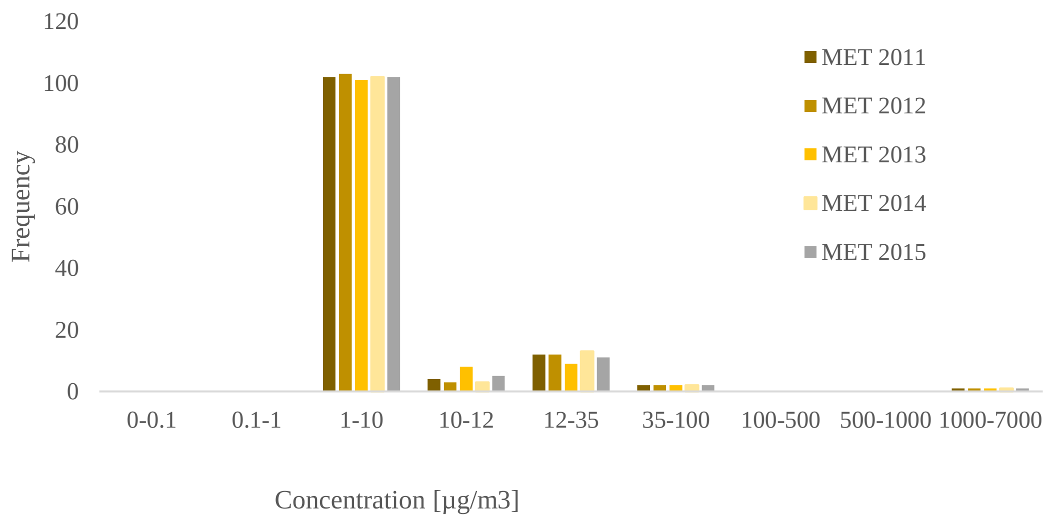


Figure 44: Frequency distribution for all years' meteorological data using 1-kilometer receptor spacing

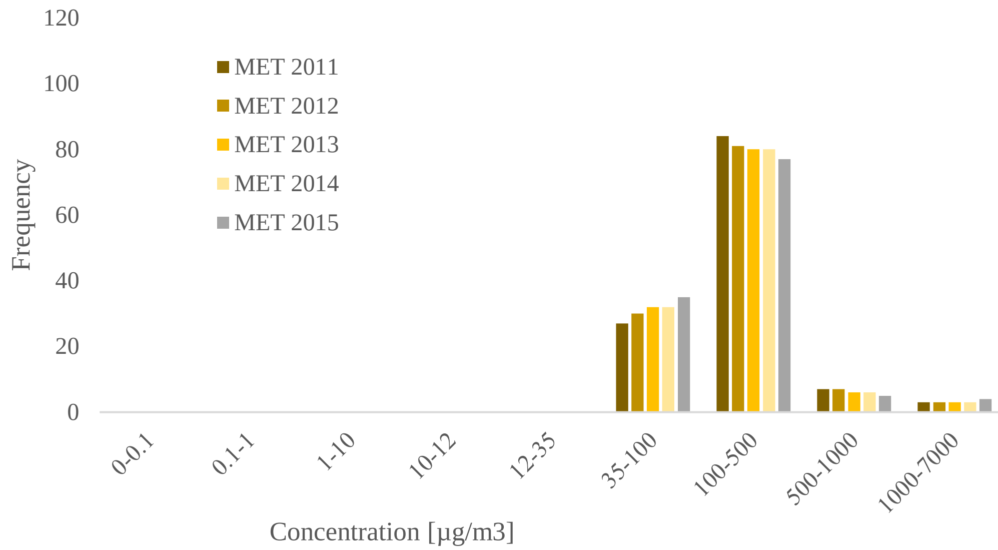


Figure 45: Frequency distribution for all years' meteorological data using 100-meter receptor spacing

Figure 43, Figure 44, and Figure 45 show the model results for each spatial scale are clumped together along the x-axis. This clustered distribution within a smaller concentration range indicates that the concentrations estimated in AERMOD are within a set range, independent of which year's meteorological data was used for each model run. These figures also show the extent to which the truck emissions disperse as the distance from the idling area increases. Figure 45 shows that in a 500-meter radius around the idling area, concentration ranges predicted by AERMOD vary from $35 - 7000\ \mu g/m^3$ with 66.4% of the model results falling in the range of $100 - 500\ \mu g/m^3$. This range is the highest concentration range predicted for any of the spatial scales and also shows the highest variation in the model performance for different years' meteorological data. These results show a similar range to the model results shown in Figure 38; however, the model performance shown in Figure 45 shows much less variation than the results with varying average vehicle age. For varying average vehicle age, 55.4% of the model results fell in the range of $100 - 500\ \mu g/m^3$ compared to 66.4% for varying meteorological years' data.

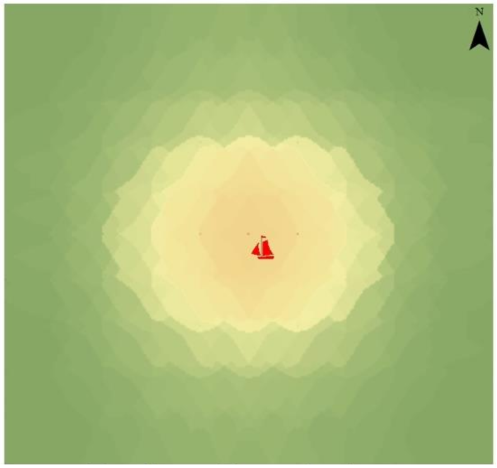
Figure 45 shows the model results for different years' meteorology have very similar frequencies for predictions falling within each concentration bin range indicating meteorology has less influence on model results than assumed average vehicle age.

Figure 44 shows the concentration range for the 5-kilometer radius around the port varies from $1 - 100\ \mu g/m^3$ with a majority of the model predictions falling in the range of $1 - 10\ \mu g/m^3$. This total concentration range excludes the concentration estimations for the receptor locations within the idling area. The overall concentration range spans one less concentration bin on either side of the range than the predictions for the same spatial scale but with varying average vehicle ages instead (Figure 37). This indicates that the model results on the same spatial scale are more clustered when meteorology varies than when average vehicle age varies. The clustering of model results in the $1 - 10\ \mu g/m^3$ concentration bin range is even more dominant for varying meteorological data with 84.3% of all model results falling in this concentration bin range compared to 64.3% of model results falling this concentration bin range for varying average vehicle years as shown in Figure 44 and Figure 37.

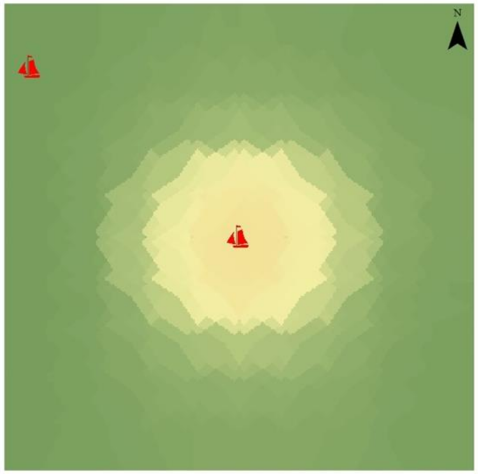
Figure 43 shows the concentration range for the 15-kilometer radius around the port varies from $0.1 - 35\ \mu g/m^3$ with 63.3% of the model predictions falling in the range of $0.1 - 1\ \mu g/m^3$. The range of concentrations estimated by the model for varying years' meteorological data is the same range predicted for the same spatial scale but varying average vehicle age. Concentration estimates were more clustered in the lower concentration bin ranges which is expected as the input areal emission rate was lower than or the same as three of model configurations for average vehicle age. The model results in the $0.1 - 1\ \mu g/m^3$ concentration bin range show that 64.3% of all model results fall in this concentration bin range and 35.2% of model results fall in the $1 - 10\ \mu g/m^3$ concentration bin range. For the model configuration with varying average vehicle age discussed in section 4.1, the model results in the $0.1 - 1\ \mu g/m^3$ concentration bin range show that 46.5% of all model results fall in this concentration bin range and 49.8% of model results fall in the $1 - 10\ \mu g/m^3$ concentration bin range. These results indicate that the model results are much more evenly divided between two concentration bin ranges for the varying average vehicle age model configuration than for the varying meteorological data model configuration meaning vehicle age has a bigger impact on model performance than meteorological data for this spatial scale.

4.3: Variations in the Roughness Parameter Used

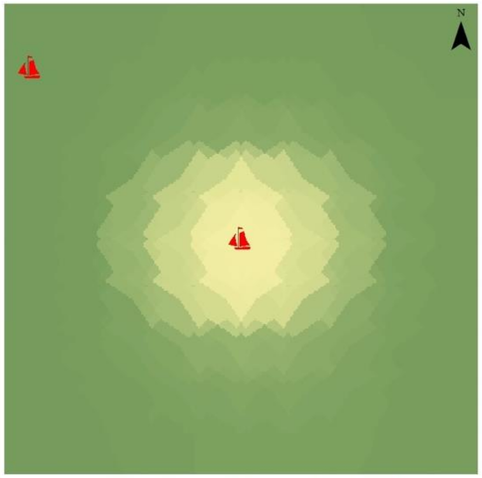
This section follows the same format as the previous section, using the receptor locations specified in Figure 32, the areal emission rates given in Table 7, the areal emission rate for a 7.5-year average vehicle age, with meteorological data from George Bush Intercontinental airport for the year 2015, and with the roughness parameter varied. The roughness parameter varied between low medium and high roughness to compare model results with different roughness parameters. The concentration field calculated by AERMOD was plotted in ArcGIS for each roughness parameter as shown in Figure 46, Figure 47, and Figure 48.



Roughness Parameter: Low
3-kilometer grid



Roughness Parameter: Medium
3-kilometer grid



Roughness Parameter: High
3-kilometer grid

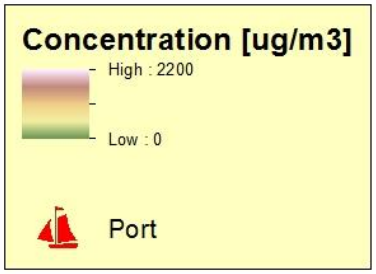
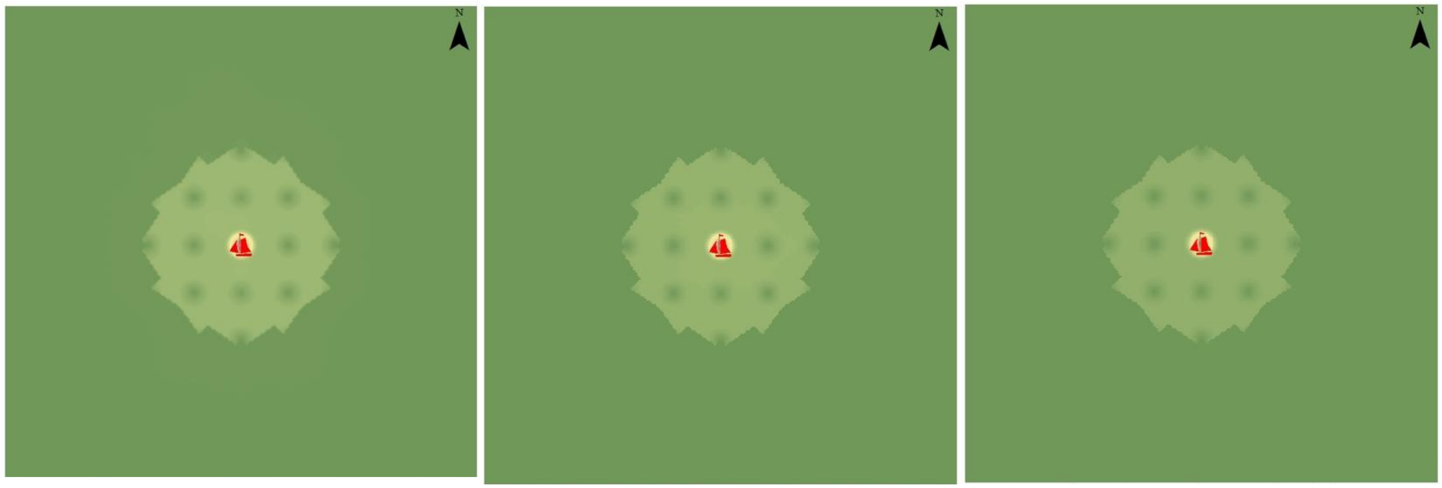


Figure 46: AERMOD results for a 15-kilometer radius surrounding the Port of Houston using 3-kilometer grid cells with 7.5-year average vehicle age in roughness parameter order: low, medium high



Roughness Parameter: Low
1-kilometer grid

Roughness Parameter: Medium
1-kilometer grid

Roughness Parameter: High
1-kilometer grid

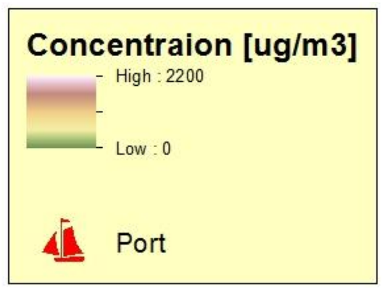
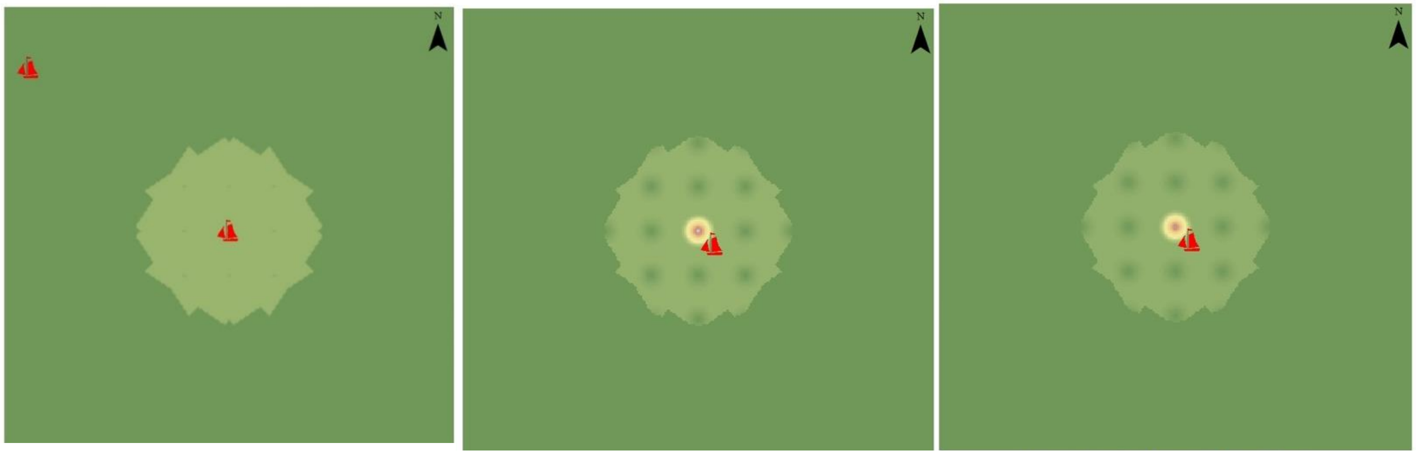


Figure 47: AERMOD results for a 5-kilometer radius surrounding the Port of Houston using 1-kilometer grid cells with 7.5-year average vehicle age in roughness parameter order: low, medium high



Roughness Parameter: Low
100-meter grid

Roughness Parameter: Medium
100-meter grid

Roughness Parameter: High
100-meter grid

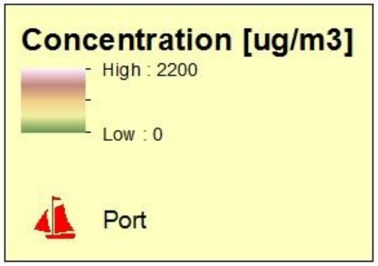


Figure 48: AERMOD results for a 1-kilometer radius surrounding the Port of Houston using 100-meter grid cells with 7.5-year average vehicle age in roughness parameter order: low, medium high

The model results using different years' meteorology were compared using frequency distribution plots as shown in Figure 49, Figure 50, and Figure 51.

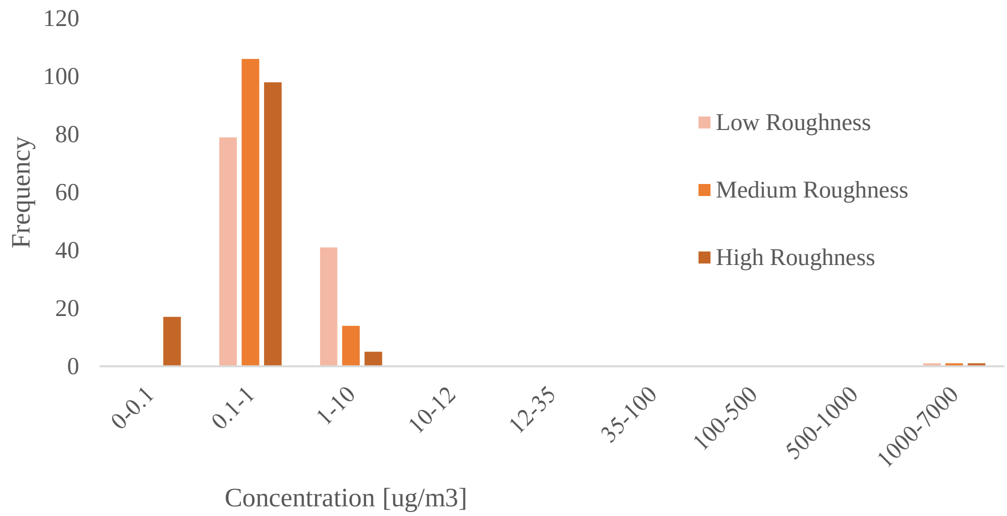


Figure 49: Frequency distribution for all roughness parameters using 3-kilometer receptor spacing

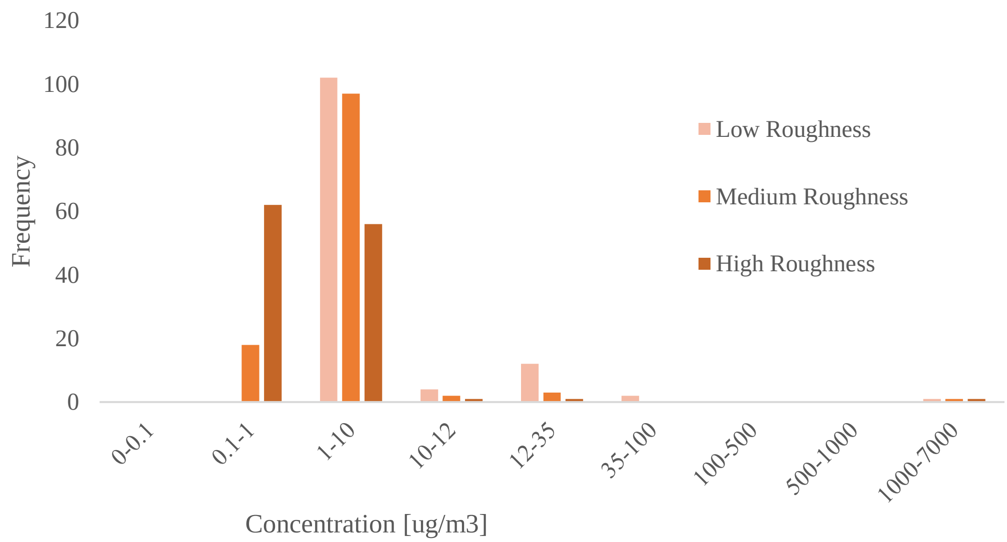


Figure 50: Frequency distribution for all roughness parameters using 1-kilometer receptor spacing

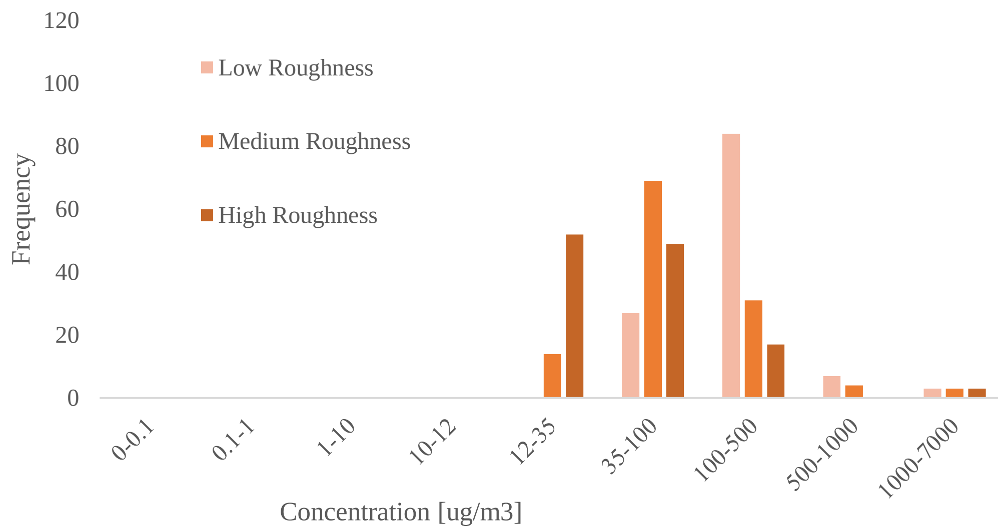


Figure 51: Frequency distribution for all roughness parameters using 100-meter receptor spacing

Figure 49, Figure 50, and Figure 51 show the AERMOD model results for each spatial scale. These figures show that as the distance from the idling area decreases, the concentrations estimated by the model increase. This indicates the extent to which the truck emissions disperse as the distance from the idling area increases. Figure 51 shows that in a 500-meter radius around the idling area, concentration ranges predicted by AERMOD vary from $12 - 7000\ \mu g/m^3$ which spans one extra concentration bin $(12 - 35\ \mu g/m^3)$ than the concentration range for varying average vehicle range and varying meteorological data. A majority of the model results fell in the range of $35 - 500\ \mu g/m^3$ with 39.9% of results falling in the $35 - 100\ \mu g/m^3$ bin range and 36.4% of results falling in the $100 - 500\ \mu g/m^3$ bin range. This range is the highest concentration range predicted for any of the spatial scales and also shows the highest variation in the model performance for different roughness parameters. These results show a similar range and variability to the model results shown in Figure 38 for varying average vehicle age but show much more variability in model performance than the results for varying meteorological data as shown in Figure 45.

Figure 50 shows the concentration range for the 5-kilometer radius around the port varies from $0.1 - 100\ \mu g/m^3$ with 70.2% of the model predictions falling in the range of $1 - 10\ \mu g/m^3$. This total concentration range excludes the concentration estimations for the receptor locations within the idling area. The overall concentration range spans one less concentration bin in the lower range than the predictions for the same spatial scale but with varying meteorological data (Figure 44) and spans one less concentration bin on the higher side of the range for the model results with varying average vehicle (Figure 37). The model results show that 70.2% of the concentrations predicted for varying roughness parameter are in the $1 - 10\ \mu g/m^3$ concentration bin range compared to 64.3% of model results falling this concentration bin range for varying average vehicle years and 84.3% for varying meteorological years.

Figure 49 shows the concentration range for the 15-kilometer radius around the port varies from $0 - 35\ \mu g/m^3$ with 78% of the model predictions falling in the range of $0.1 - 1\ \mu g/m^3$. The results for varying average vehicle age were much more evenly split between the $0.1 - 1\ \mu g/m^3$ concentration bin range and the $1 - 10\ \mu g/m^3$ concentration bin range. For varying meteorological data, only 63.3% of the model predictions fell in the range of $0.1 - 1\ \mu g/m^3$. This indicates that for the spatial scale of 15-kilometers around the port, the model results for varying roughness parameter showed the least variation in comparison to varying meteorological data and varying average vehicle age.

5. CONCLUSION

The work presented in this thesis is done in support of a larger research effort to estimate emissions generated by four sectors of port operations: shipping, freight handling, rail operations, and trucking operations. The findings from this thesis will allow the CARTEEH project team to create a study methodology and data analysis plan that best fits their purposes and gives the best insight into population exposures related to port emissions.

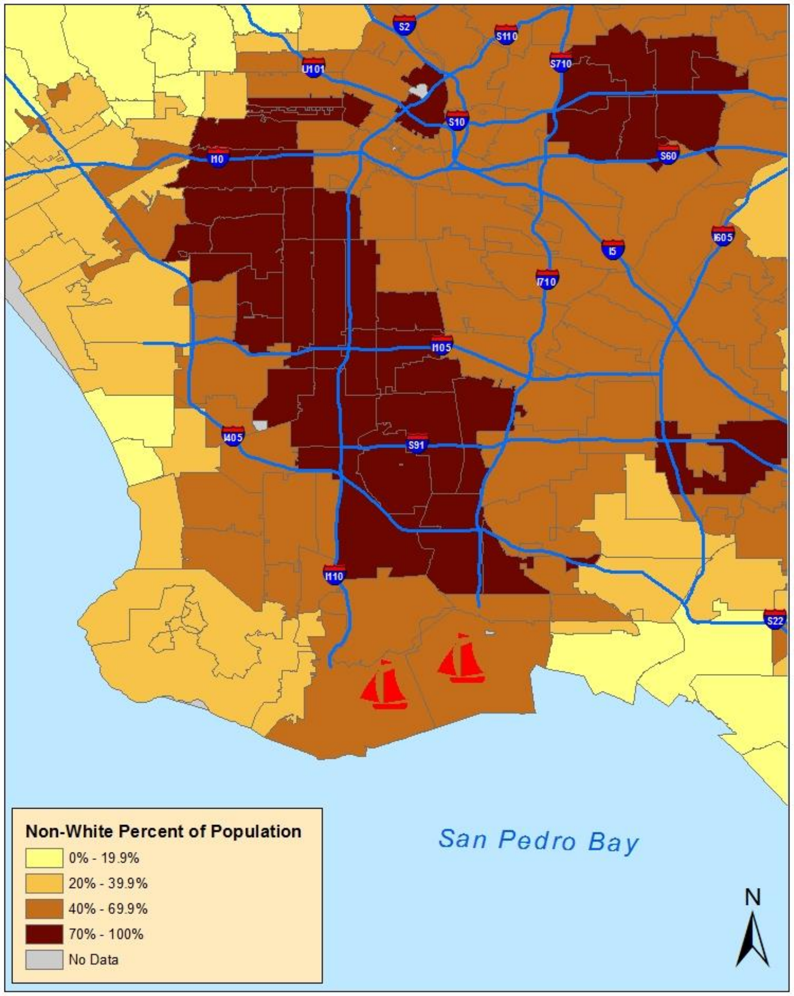
The results from the population demographics mapping section indicate that minority populations and low-income populations are the most prevalent disadvantaged populations living around the ports included in this study. These parameters are two characteristics mandated in the Environmental Justice analysis guidance document. Household size is also higher in areas surrounding the port. Disadvantaged populations in terms of education, age, and linguistic isolation are not noticeably prevalent in higher proportions in the areas surrounding the ports studied.

The dispersion modeling component of this analysis includes emissions modeling in AERMOD on three different spatial scales. The estimated concentrations were then mapped using ArcGIS's kriging interpolation tool. The modeling portion of this thesis evaluates the effect vehicle age, meteorological data, and characterization of the roughness parameter has on estimated concentrations. The AERMOD results showed that vehicle age has the biggest impact on estimated concentrations from idling emissions outside of port gates as the model results showed the greatest variability when average vehicle age varied. In spite of vehicle age showing the greatest variability in the model results, this does not indicate that vehicle age data needs to be collected as part of the CARTEEH Ports Project study methodology, as the model performance was still consistent across varying average vehicle age.

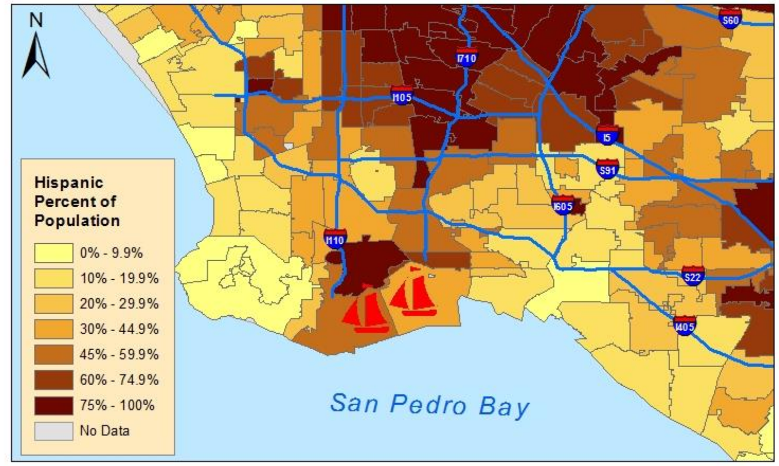
When comparing the model variability for different meteorological years' data and different roughness parameters, the model results were more consistent with varying years' meteorological data than with varying roughness parameter. This indicates that generating temporally accurate meteorological data is less important when looking at pollution dispersion over an entire year's concentration predictions.

APPENDIX

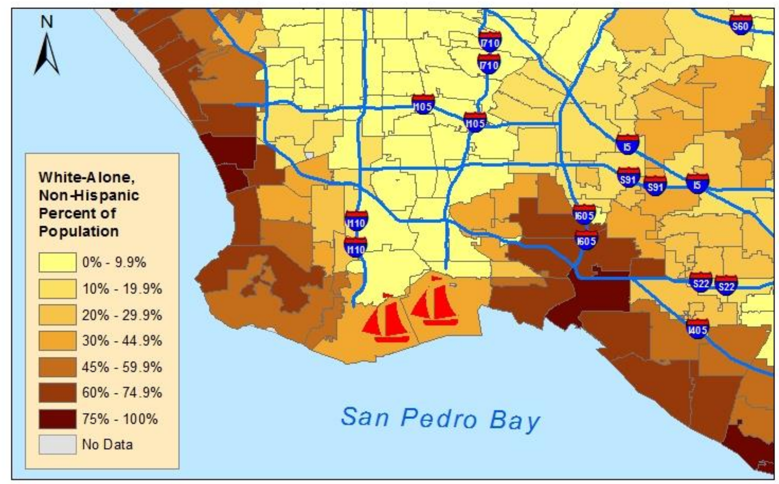
The figures presented in this section of the report were created using information provided by the U.S. Census Bureau and include further subdivisions of the racial demographics of each study area. The information presented in the maps in this section are presented as three subplots for each port/state. The subplots are presented in the same format and present the same information for each state. The information presented in each map for racial spatial variation includes: non-white percent of the population (sub-plot A), Hispanic percent of the population (sub-plot B), and white-alone, non-Hispanic percent of the population (sub-plot C).



A. Non-White Population



B. Hispanic Population



C. White-Alone, Non-Hispanic Population

Figure 52: Population demographics for race in census block groups surrounding the Ports of Los Angeles and Long Beach

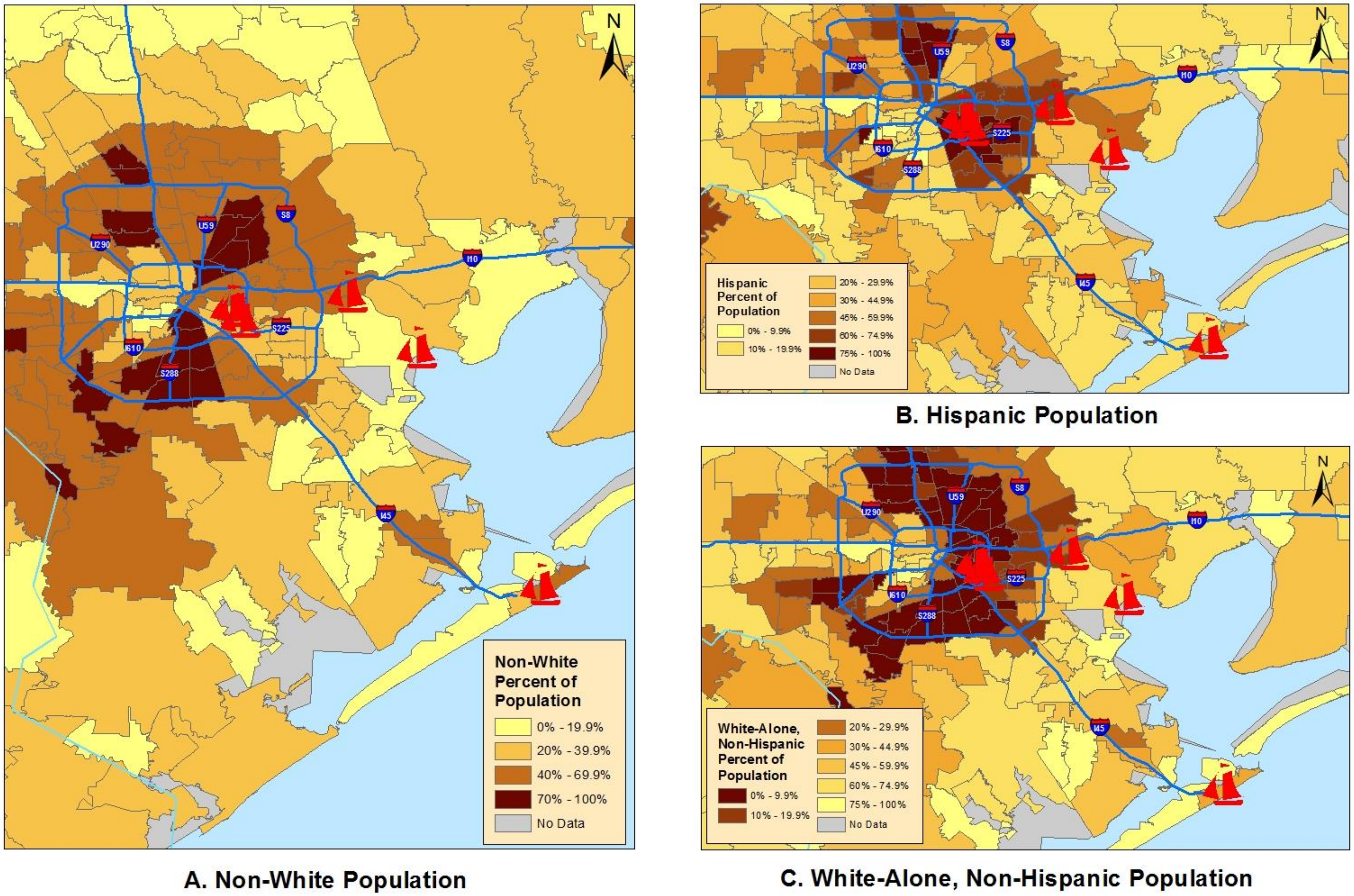
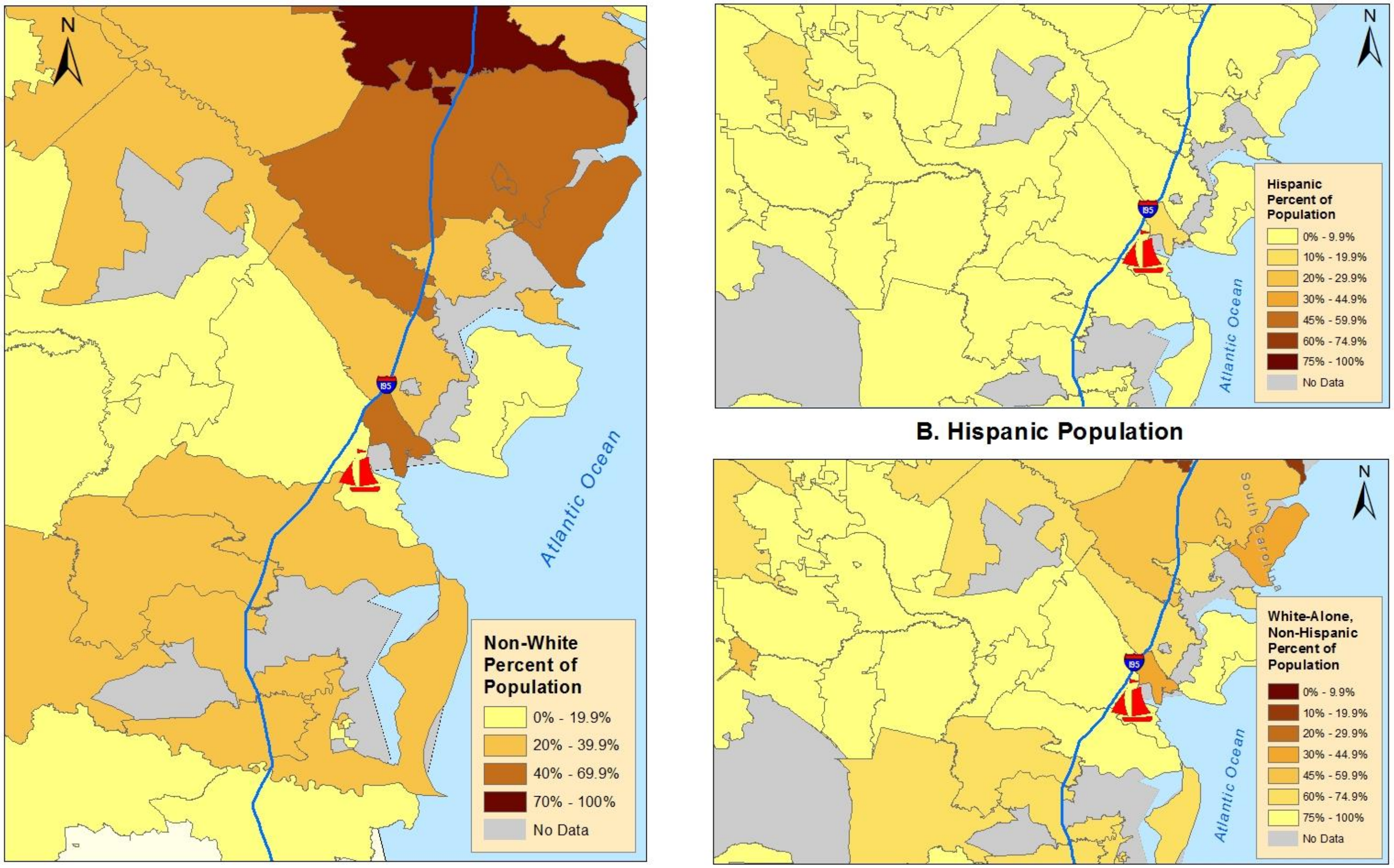


Figure 53: Population demographics for race in census block groups surrounding the Port of Houston



A. Non-White Population

B. Hispanic Population

C. White-Alone, Non-Hispanic Population

Figure 54: Population demographics for race in census block groups surrounding the Port of Brunswick

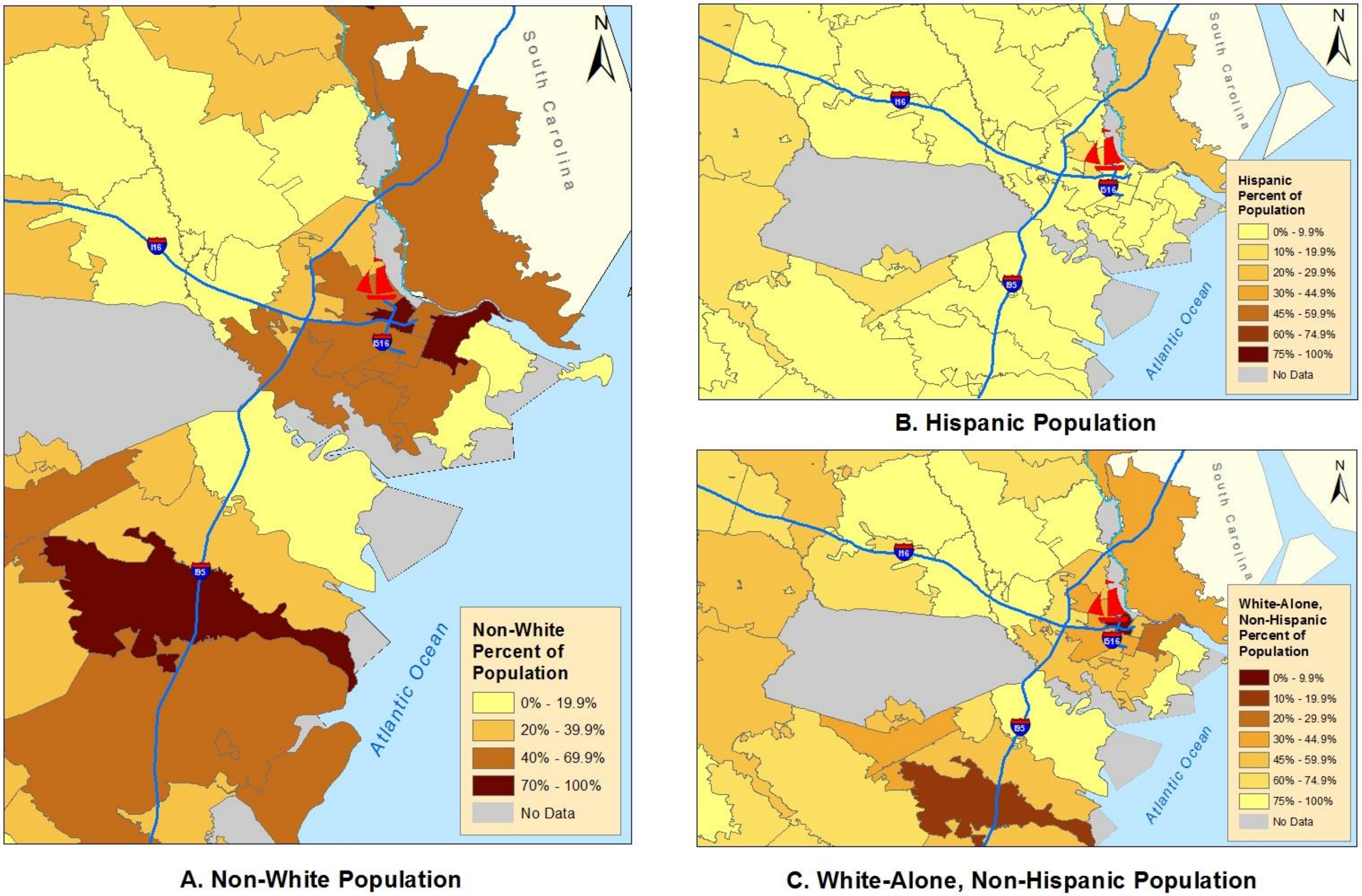


Figure 55: Population demographics for race in census block groups surrounding the Port of Savannah

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